Consumer Perceptions of Artificial Intelligence Avatars: Linking Cognitive Evaluations to Behavioural Responses

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A thesis submitted in partial fulfilment of the requirements for the degree of
Master of Commerce in Marketing
Department of Management, Marketing and Entrepreneurship

Josh Mark Ryan
University of Canterbury
2021

Primary Supervisor: Professor Paul Ballantine

Secondary Supervisor: Professor Girish Prayag

Abstract

The purpose of this research was to understand the direct effects of multiple AI (artificial intelligence) genders, purchase types, and anthropomorphised levels (environmental stimuli), on consumers' cognitive, and behavioural response to AI. The research adopts an experimental design, to understand the influence of environmental stimuli on participants' cognitive and behavioural responses using a 2 x 2 x 2 between-subjects factorial design. The experiment exposed participants to one of eight manipulations of the studies' three independent variables ("purchase type," "AI gender," and "anthropomorphism level"). Amazon's Mechanical Turk was utilised to recruit participants for both the pre-test and the main study using a questionnaire that was designed and distributed through Qualtrics. Initially, 644 participants were sampled for this experiment but after data cleansing, the sample size was reduced to 612. A three-way ANCOVA, independent t-test, linear regression, and structural equation model (SEM) analyses were conducted to test the studies' three main hypotheses. The results indicated that the manipulation of the three independent variables significantly affected participants' usage and purchase intention (behavioural responses), and one cognitive response (website credibility). Furthermore, the linear regression analyses indicated that four cognitive responses were found to significantly predict participants' behavioural responses. However the results of SEM identified three cognitive responses (website believability, website sense of presence and technology helpfulness) as having a significant effect towards predicting participants' behavioural responses. The last key finding was the influence of the control variable of user overall mood, the results found that users mood significant effected all five cognitive responses and both behavioural responses. Lastly, the managerial and theoretical implications are discussed, along with research limitations and suggestions for future research.

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Acknowledgements

First and foremost, I am profoundly grateful to both of my supervisors Paul Ballantine and Girish Prayag for your guidance, advice and overall help over the course of my thesis. None of this would have been possible without you.

Thank you Mum and Dad for all of the help, advice and constant support throughout my entire time at University. You were both always there for me and I wouldn’t have been able to achieve this without you both.

Thank you to my sister Amy for your constant support and advice throughout this experience.

Thank you to my Partner Elizabeth for always being there for me, for supporting and making sure I stayed true to myself. This wouldn’t have been possible without you.

Thank you to my friends for all of the good times and distractions that were required to get myself through this experience.

Lastly, I would like to thank my entire 2020 Cohort, it was a pleasure going through this with all of you, I wish you all the best of luck going forward.

Chapter 1. Introduction

1.1 Introduction

Since the creation of human-computer-interaction (HCI) in the 1980s, its purpose has been to design and develop interactive computer systems that are efficient and easy to use, so people within society can efficiently access the benefits computer-based tools present (Card, 2018). Successful HCI creates software or technology that is both usable and useful for completing the task it was developed for (Ackerman & Mainwaring, 2005; Bannon, 1995; Carroll, 1997; Fischer, 2001; Olson & Olson, 2003). The context and purpose of this research was to understand consumer perceptions of artificial intelligence (AI) in an online marketing environment. The evolution of AI has granted marketers new technological advances with which to improve their digital marketing abilities, through the continued use and evolution of virtual assistants, cloud services, mobile communication, wearable devices, and personalised advertisements (Kim et al., 2019; Mari et al., 2020). Artificial Intelligence has and will continue to change technology as we know it over the next 10 to 20 years. Artificial intelligence can assist marketers in numerous ways, by improving the process of “drawing conclusions from unstructured data about causes and effects within extremely large data sets” (Campbell et al., 2020, p. 231).

The key purpose and objective of this research was to understand the impact of multiple environmental stimuli (AI manipulations) on participants’ cognitive and behavioural responses. The environmental stimuli were created by manipulating three independent variables (purchase type, AI gender, and anthropomorphism level), which created eight experimental conditions, to understand the variations in participant responses. Five cognitive responses were analysed: website credibility, website believability, website sense of presence, website involvement, and technology helpfulness. Consumers’ usage and purchase intentions (behavioural responses) were measured to understand the direct effect of the environmental stimuli and cognitive responses on participants’ behavioural responses. Lastly, the control variable of users’ overall mood was analysed to understand 1) the effects of mood prior to the experiment on their views of the AI software, and 2) the resulting impact on participants’ behavioural responses.

Thus, this research set out to extend the current AI and marketing literature by identifying how the evolution of AI could be developed to be both usable and useful for consumers, to inform the body of literature and future AI developers.

1.2 Creation of a Conceptual Framework

The conceptual framework of this research was created by combining aspects of the stimulus-organism-response (SOR) framework and technology acceptance model (TAM) to understand how multiple environmental stimuli affect consumers' cognitive and behavioural responses. The SOR framework has been widely used to research online user behaviours in experimental research (Cao et al., 2019; Zhai et al., 2020; Zhang & Xu, 2016). The technology acceptance model identifies perceived usefulness and perceived ease of use as two key cognitive responses to form an attitude towards using a system, which in turn, leads to a behavioural response to the actual system usage (Davis, 1985; Legris et al., 2003; Porter & Donthu, 2006).

To add context to this research and to the combined use of SOR and TAM, the three independent variables used in the research were manipulated to create eight experimental condition (presented in Table 1.1). The three variables explored within the research were "multiple AI purchase types" (hedonic and utilitarian travel itineraries), "multiple anthropomorphism AI levels" (high and low), and "multiple AI genders" (male and female).

Table 1.1: *Experimental Conditions*

<table>
<tr><th rowspan="2">AI gender</th><th rowspan="2">Purchase type</th><th colspan="2">Anthropomorphism Level</th></tr>
<tr><th>Low anthropomorphism (No avatar)</th><th>High anthropomorphism (Human-like avatar)</th></tr>
<tr><td rowspan="2">Male</td><td>Hedonic</td><td>Condition 1</td><td>Condition 5</td></tr>
<tr><td>Utilitarian</td><td>Condition 2</td><td>Condition 6</td></tr>
<tr><td rowspan="2">Female</td><td>Hedonic</td><td>Condition 3</td><td>Condition 7</td></tr>
<tr><td>Utilitarian</td><td>Condition 4</td><td>Condition 8</td></tr>
</table>

The eight experimental conditions were created and used to test their impact on the five cognitive responses (dependent variables), to understand how the cognitive responses affected participants’ behavioural responses (purchase and usage intentions) in relation to AI. The elements of the conceptual framework and their correlating sub-objectives tested are presented in Table 1.2.

Table 1.2: *Conceptual Framework Characteristics*

Framework characteristics	Sub-objectives (in relation to study)
Environmental stimuli (Ryan’s Travel website)	AI gender (male and female) Purchase types (hedonic and utilitarian) Anthropomorphism level (high and low)
Cognitive response (perceived usefulness and perceived ease of use)	Website credibility Website believability Website sense of presence Website involvement Technology helpfulness
Behavioural response	Usage intention Purchase intention

This was aimed at understanding which of the three environmental stimuli had the greatest effect on increasing participants’ purchase intentions, as well as their intentions to use AI. The control variable of users’ overall mood was tested due to assumptions found in the literature on experimental design. The assumption was that participants’ positive and negative moods have been shown to affect their experience with the environmental stimuli they were subjected to; negative moods increase a participant’s likelihood of appraising a stimulus negatively, whereas positive moods increase the likelihood of appraising a stimulus positively (Schmid & Mast, 2010). It was expected that the poorer a user’s overall mood, the lower their purchase and usage intention would be, compared to that of users with a better overall mood.

1.3 Literature Gaps and Research Justification

Artificial intelligence is an old but undiscovered concept established in 1956 and “remained an area of relative scientific obscurity and limited practical interest for over half a century” (Haenlein & Kaplan, 2019, p, 5). Although the concept has been around for over 60 years, due to technological limitations from 1956 to the early 2000s, much of what had been theorised could not be created due to the limitations in data storage and a lack of other key developments. Artificial intelligence is still a relatively new research area, with very little literature confirming how and why consumers are able to adapt to AI in an online context.

Pelau and Ene (2018) explained that technological development such as computers, the internet, and mobile phones, has allowed humans to live more efficiently and conveniently; AI is thought to be the next great technological advance (Darko et al., 2020). However, it is notable that little research has been conducted on how consumers may adopt AI. This research intended to fill multiple gaps in the extant literature by creating an understanding of the optimal manipulation of each of three independent variables (purchase type, AI gender, and anthropomorphism level) to understand their effects on participants' behavioural responses. The following sections present the various literature gaps found in the marketing and AI literature, and that formed the basis of this research.

1.3.1 Artificial Intelligence Gender

Gender stereotypes of virtual avatars (social robots) have been studied to understand their effect on consumer adoption intention. Previous studies have explained that "the gender and personality of social robots do not monotonically influence user responses; instead, they interact with corresponding role stereotypes to affect user acceptance of social robots." (Tay et al., 2014, p. 75). Tay et al. (2014) expanded the need for this research, by stating the need for future research to explore the effects of role stereotypes in other types of social robots. This future research suggestion was acted on by Wirtz et al. (2018), who explained that issues of robot gender and personality are likely to impact consumer adoption responses, and preferences may depend on context-dependent stereotypes. Consumers were found to prefer AI that had matching genders, personalities, and occupation role stereotypes. Female AI was found to influence positive affective evaluations, increased perceived behavioural control, and greater acceptance of female healthcare AI compared to that of male healthcare AI. However, the inverse was found in security robots, as male AI was found to influence positive evaluations, increase perceived behavioural control, and greater acceptance toward male security AI compared to that toward female security AI (Tay et al., 2014).

The impact of gender in an online purchasing context has previously been studied to understand the difference in both the gender of a virtual avatar and of a user, on purchase intention and usage intention of a website (Chiu et al., 2005; Garbarino & Strahilevitz, 2004). However, there is no significant understanding yet, of how the gender of AI can affect a user's adoption intentions of a technology; this research attempted to understand this effect and fill the gap within the AI and marketing literature.

Artificial intelligence has been in development since 1956, and since then, many stereotypes have arisen: "in this process their (consumers') interactions also reveal a biased view of gender, as these ubiquitous companions perform tasks that echo historically feminine roles and articulate these features with stereotypical behaviours" (da Costa, 2018, p. 69). Furthermore, it is possible that females, on hearing a male voice, may react to the message differently than do males hearing a male voice (Hanus & Fox, 2015); this is a research avenue that this research also set out to address. Gender of the user has been shown to have an effect on purchase intention, as female buyers have been found to have stronger repeat purchase intentions than have male buyers. This finding confirms that of previous studies that found females have stronger repeat purchase intentions than do men in an online setting (Chiu et al., 2014; Forsythe & Shi, 2003). Understanding how male and female AI genders and the gender of a user impact a consumer's cognitive and behavioural responses was a key interest of this research.

1.3.2 Hedonic and Utilitarian Purchase Types

The impact of hedonic and utilitarian purchase types on consumers' purchase intentions in an online context has been the focus of previous research (Chiu et al., 2014; Sarkar & Sarkar, 2019; Sun & Spears, 2012). This study sought to fill a gap in the literature, by creating an understanding of how hedonic and utilitarian purchases affect consumer purchase intention on and usage intention of a website, using multiple variables such as consumer involvement, a sense of presence and the helpfulness of technology.

Hedonic software alters consumer delight through the promotion of emotions, however, utilitarian software alters consumer satisfaction through the prevention of emotions (Chiu et al., 2014). The helpfulness of technology has been shown to have significant effects on consumer purchase intention (Sarkar & Loureiro, 2013). Chiu et al. (2014) suggested that future research should examine how the helpfulness of hedonic and utilitarian purchases influence consumers' behavioural responses in an online shopping context. This study attempted to fill this gap in the literature by determining how hedonic and utilitarian purchases affect consumer purchase intention in an online context.

Sarkar and Sarkar (2019) found that consumers perceive software to be either hedonic or utilitarian, and the perceived design was shown to impact a consumer's involvement with the software. However, a limitation of Sarkar and Sarkar's (2019) study was that their sample focused its investigation on young consumers' relationships with software, a limitation also highlighted by Sun and Spears (2012). Therefore, this study ensured a wider sample was utilised, to understand how a consumer's age and hedonic and utilitarian software design impacts consumers' purchase and usage intentions.

1.3.3 Level of Anthropomorphised Artificial Intelligence

Artificial intelligence continues to integrate into our daily lives, and the development of AI technology has seen virtual assistants evolve further towards the social realm becoming more anthropomorphised, and viewed less as an assistant and more as a companion (da Costa, 2018). Numerous studies have noted the importance of future research on AI systems and the degrees of anthropomorphism required to influence consumer behavioural responses (Kääriä, 2017; Pantano & Pizzi, 2020; Pelau & Ene, 2018; Thüring & Mahlke, 2007; Wirtz et al., 2018).

The attribution of human-like characteristics has been consistently shown to have a positive impact on consumers' purchase and usage intentions (Benbasat, 2010; Nowak, 2000; Sheehan, 2018; Waytz et al., 2014; Yuan & Dennis, 2017; Złotowski et al., 2015). Studies have found that the more anthropomorphised a technology was, the greater the user would hold the actions of the technology accountable for its service, but a higher level of anthropomorphism led to more positive interactions between the user and the technology (Waytz et al., 2014; Złotowski et al., 2015). Nowak (2000) argued that her results showed that an agent or avatar with a strong anthropomorphic image was perceived as more credible, likable, and co-present, compared to that of a weaker anthropomorphic agent or avatar. The inclusion of facial features on a non-human object was also found to have a greater impact on adoption than was adding human-like voices to a non-human object (Yuan & Dennis, 2017). Similarly, Benbasat (2010) explained that "humanoid avatars used as the interface to an advice-giving agent should match the users in gender and ethnicity to enhance the agent's adoption" (p. 17).

Fernandes and Oliveira (2020) suggested that service robot acceptance considering other conversational agents or other service robots (e.g., humanoid or embodied forms), should be studied to understand the optimal level of anthropomorphised virtual avatars (Fernandes & Oliveira, 2020). Consistent with this, Pantano and Pizzi (2020) suggested that "more research is needed to understand whether and to what extent the innovative features of conversational agents highlighted by the present research are going to significantly affect customer interactions and usage" (p. 7). Understanding what aesthetically pleasing software is, has been extensively debated; Wirtz et al. (2018) also called for more research to understand which consumer and contextual factors determine the optimal level of humanoid appearance for service robots.

Thüring and Mahlke (2007) explained that anthropomorphism plays an important role in identifying the likelihood of a user's appraisal of a website or technology positively. Moreover, Kääriä (2017) found anthropomorphism had only a small influence on intention to use the technology, and that perceived usefulness, perceived ease of use, and system quality, were still the most significant indicators of user intention.

The differences in the discussed literature indicate the need to delve further into this problem to truly understand the effect of anthropomorphism on consumers' behavioural responses to AI in an online shopping context.

1.4 Research Objectives

This research attempted to answer the main research question:

> *What are the effects of multiple purchase types, AI genders, and anthropomorphism levels (environmental stimuli), on consumers' cognitive and behavioural responses to AI?*

The following research objectives were therefore developed:

- **Objective 1:** To determine how the relationship between AI gender, anthropomorphism level, and purchase type, affect consumers' purchase and usage intentions in relation to engaging with AI.
- **Objective 2:** To determine how the relationship between AI gender, anthropomorphism level, and purchase type, affect consumers' cognitive responses in relation to engaging with AI.
- **Objective 3:** To determine if a consumers' cognitive response could be used to predict their purchase and usage intentions in relation to engaging with AI.
- **Objective 4:** To identify: the AI gender (male vs female); purchase type (hedonic vs utilitarian); and AI anthropomorphism level (low vs high); that is the most influential in increasing consumers' purchase and usage intentions in relation to engaging with AI.
- **Objective 5:** To understand the effect of consumers' overall mood on their purchase and usage intentions in relation to engaging with AI.

1.5 Research Methodology

This research was interested in identifying the most influential manipulation of multiple variables that influence consumers' adoption of AI. This understanding was developed by understanding consumers' direct response to different AI genders (male and female), purchase types (hedonic and utilitarian) and anthropomorphism levels (low and high), while also understanding how a users' overall mood at the time of the experiment influenced consumers' behavioural responses to AI technology. The research adopted a 2 x 2 x 2 between-subjects factorial design to understand the influence of multiple environmental stimuli and control variable on participants' cognitive and behavioural responses to AI in an online shopping context. Multiple statistical analyses were conducted to test the research hypotheses, and included a three-way ANCOVA, independent t-tests, linear regression, and structural equation modelling (SEM).

The sample was made up of 644 participants which was reduced to 612 after data cleansing, the sample was recruited using Amazon's Mechanical Turk (MTurk), an online workforce used for recruiting high quality research participation. MTurk is widely considered to be a revolutionary tool with the potential to transform behavioural research, specifically experimental research, as it can run experiments with a large number of participants in a previously unheard of time (Crump et al., 2013). The marketing literature has attested to the high validity found in studies using MTurk data, and MTurk has been found to produce a more diverse sample than does other online and traditional participant sources, by rapidly collecting high quality reliable data (Fritzlen et al., 2019; Nicksic et al., 2017). MTurk samples have been found to be more representative of the general population (Hulland et al., 2018), and the utilisation of MTurk was found to have no impact on participants' cognitive dissonance compared to traditional experimental research (Fritzlen et al., 2019). MTurk is the perfect research instrument for this research, due to the nature of the experiment, the resources available, and the justification found in the marketing literature for its use. Furthermore, the survey for this study was hosted by Qualtrics, an online survey tool that was used to gain an understanding of participant attitudes towards environmental stimuli, to create an understanding of their cognitive and behavioural responses.

1.6 Research Contributions

1.6.1 Theoretical Contributions and Implications

This research produced a number of theoretical contributions and implications. Firstly, an environmental stimulus that users are subjected to must serve a purpose to influence users' behavioural response, all aspects of the software design must match the exact context and industry that the AI is created for. Secondly, ensuring a well-rounded environmental stimulus is created is vital in ensuring positive behavioural responses are influenced. The initial analyses within this research discovered that individually the three independent variables were not effective in impacting users behavioural and cognitive responses when interpreted individually, however when interpreted as a whole a positive response was identified. Leading to the knowledge that users require multiple stimuli characteristics that correlate positively together to influence their responses to an AI software.

The impact of users mood was already understood, as explained by Schmid and Mast (2010). However, this research found that both behavioural responses and all five cognitive responses were heavily impacted by a user's mood prior to being subjected to the service. Identifying that a user's mood may be one of the largest barriers to influencing users experience with an AI software. Lastly, this thesis identified the need for an all-inclusive AI service to successfully influence users behavioural responses. A highly useful, and easy to use service is crucial to ensure no negative perceptions are created by a user, as these may ultimately influence their entire experience.

1.6.2 Managerial Contributions

Four key managerial contributions were created within this research. First was the understanding of the required characteristics given to AI developers and companies. When creating and developing an AI, developers and companies must first understand what it is they are attempting to create the AI for, and then designing the AI to possess the same characteristics that would be found from a human being within the same industry. Developing a personalised AI with a context in mind to match will increase the likelihood of adoption occurring through users positive behavioural responses. Secondly, the creation of the environmental stimuli of an AI is vital for AI developers and AI companies to create a credible software, which is essential for the continued use and success of an AI. Website credibility was found to be influenced by the accurate development of the environmental stimuli, ensuring that the look and feel of the AI is relevant to the context is vital to ensure users credibility perceptions are positively influenced. Next, AI developers and companies must ensure that the AI they are offering is all-inclusive. This research identified that positive behavioural responses are achieved by ensuring the AI is believable, creates a strong sense of presence, and is helpful towards fulfilling each users' purpose. Creating an AI that is both useful and usable is vital to ensure behavioural responses are positively affected.

The last major managerial contribution for AI developers and companies is the extreme importance of a user's overall mood prior to using an AI. This research discovered that both behavioural responses, and all five cognitive responses were heavily impacted by a user's positive and negative mood. With pleasant moods increasing positive experiences, and negative moods influencing negative experiences. Due to the stereotype currently surrounding AI, any errors found within its service are met with harsh criticism when compared to traditional services. Therefore, ensuring a user is in a good mood may alleviate this stereotype. AI developers and companies may benefit from implementing mood enhancers within their service. Initially developers of AI may consider using fewer ads on their sites, ensure sales are heavily presented or create a nice and comforting AI experience while the technology is still in the early adopters' stage of the technologies lifecycle. A less invasive service will allow users to see the benefits of AI rather than look for the negatives, and overall increase users behavioural responses.

1.7 Thesis Outline

This thesis consists of five chapters. This first chapter's purpose was to introduce the fundamental literature that this research was based on, while providing a justification for the conceptual framework developed for the research. It also identified the gaps in the literature, introduced the key constructs to be studied, and presented the objectives and aims that this research sought to address.

Chapter Two presents the literature review for the study. This chapter first explains the purpose of the study, identifies the key constructs, and presents the conceptual framework of the study. A short explanation of the stimulus-organism-response framework and technology-acceptance model is discussed, with their implications for the conceptual framework. Following this, each stage of the conceptual framework is discussed with the relevant literature for each stage. Lastly, a discussion on users' overall mood and its role as the control variable of the research is explained.

Chapter Three, the methodology, outlines the methods used for this research. The development of the online experiment, AI videos, sampling procedures, and questionnaire are fully explained, followed by the results of the pre-test and the corresponding adjustments to the final experiment and questionnaire.

Chapter Four presents the results of the experiment, including the results of the manipulation checks and scale reliability testing. The results from the statistical analysis were used to test the hypotheses presented in Chapter Two, using a three-way ANCOVA analyses, independent t-tests, linear regression, and a structural equation model.

Chapter Five presents the discussion and conclusion to the study. This chapter discusses the key research findings, and identifies the research implications and contributions, the limitations of the study, and recommendations for future research.

Chapter 2. Literature Review

2.1 Introduction

The purpose of this chapter is to provide a detailed overview of the literature informing the basis of this research. First, the key constructs are defined and presented in Table 2.1, followed by the theoretical model of the research. This conceptual model is grounded in different aspects of the SOR and TAM frameworks, to support the hypotheses of the study. For example, SOR's environmental stimuli dimension is integrated with TAM's user motivation aspects (cognitive and behavioural responses), to understand AI developments' usefulness and usability. Next, the first stage of the conceptual framework is discussed, by explaining the three independent variables' (purchase type, AI gender and anthropomorphism level) direct effects on users' behavioural responses (usage and purchase intentions). Next, the second stage of the conceptual framework is discussed, with the presentation of the five cognitive responses (website credibility, website believability, website sense of presence, website involvement, and technology helpfulness), with literature explaining the effects of purchase type, and AI gender and anthropomorphism level on each cognitive response. Following this section, the final stage of the conceptual framework is presented, by explaining the effects of the five cognitive responses on users' behavioural responses (usage and purchase intentions). Finally, the covariate of user overall mood is discussed, followed by the chapter summary.

2.2 Research Key Constructs

Table 2.1 presents the key construct definitions of this research:

Table 2.1: *Key Constructs*

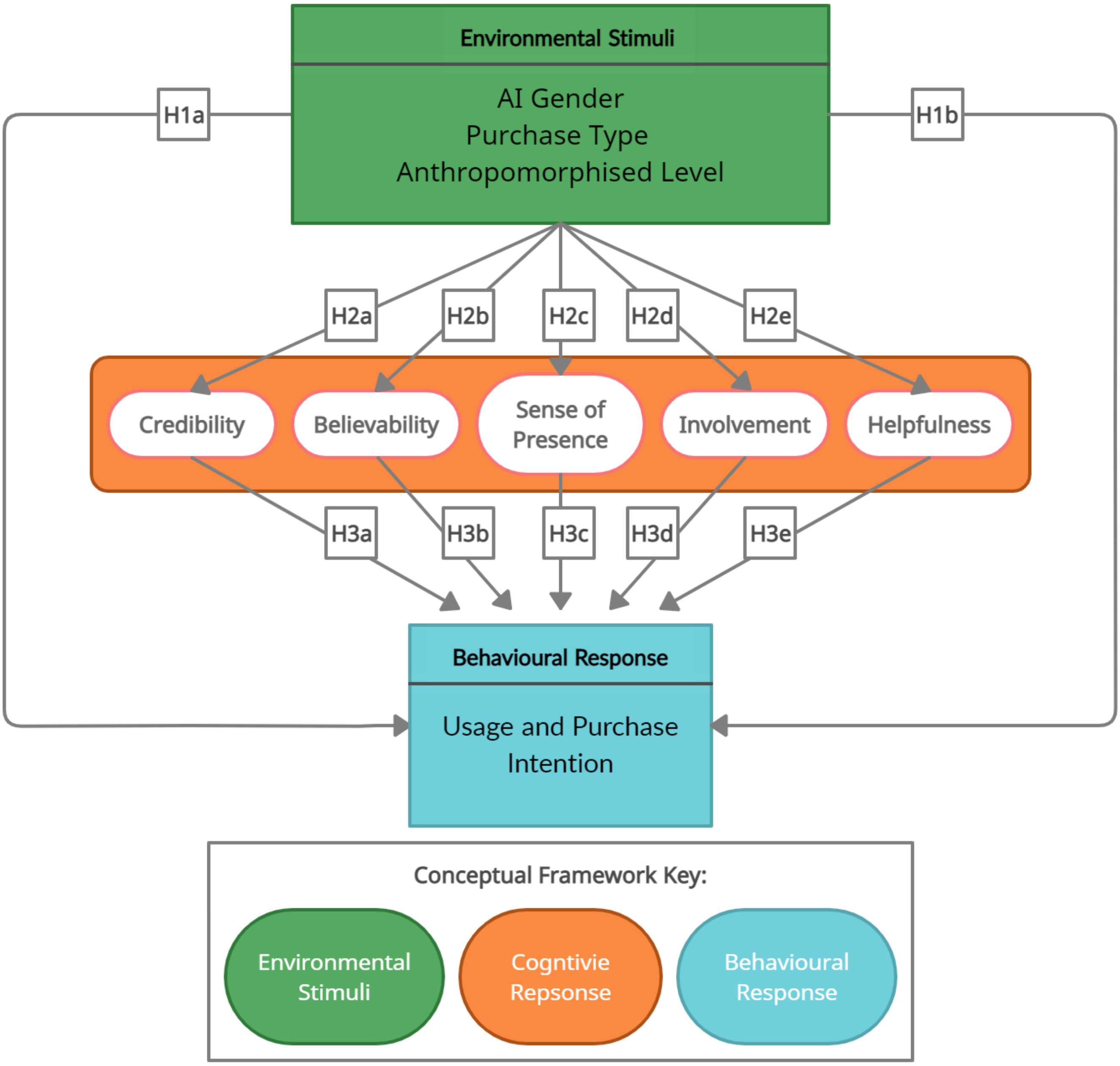
Key Constructs	Definition
Artificial intelligence (AI)	*Artificial intelligence* is a system's ability to correctly interpret external and internal data (inputs), to learn from such data and to use that learning to achieve specific goals and tasks through flexible adaptation (outputs) (Kaplan & Haenlein, 2019).
AI gender	This is the gender of the avatar itself (Zhang et al., 2017). (The two types of AI gender are male and female).
Purchase type	*Purchase type* (task definition) is the consumer's process of evaluating information and its influence on different kinds of consumption

	behaviour. This process involves goal directed activities of searching for information, retrieving memory cues, weighing evidence, and arriving at a clear and considered purchase evaluation (Holbrook & Hirschman, 1982). Two evaluations can be created: a hedonic purchase or a utilitarian purchase.
Hedonic purchase	A *hedonic purchase* is characterised as an affective and sensory purchasing experience of aesthetic pleasure. This occurs by providing consumers a product/service that entices fantasy fulfilment, perceived freedom, heightened arousal, and enhancement of positive emotions (Alzayat & Lee, 2021).
Utilitarian purchase	A *utilitarian purchase* is characterised as consumption that is more cognitively driven, instrumental, and properties oriented, and occurs by providing consumers a product/service that is concerned with the functional outcomes derived from the consumption experience (Alzayat & Lee, 2021).
Anthropomorphism	*Anthropomorphism* is the attribution of distinctively human-like feelings, mental states, and behavioural characteristics to inanimate objects or animals (Airenti, 2015; Salles et al., 2020).
Anthropomorphised AI level	*Anthropomorphised AI level* is the variation of the talking avatar, voice and other visual aspects of a virtual avatar (Gong, 2008), and defined within this research as “high” and “low” anthropomorphism.
Credibility of website	*Website credibility* is the judgment made by a user concerning the believability of a website, and the belief that information found on the website is true and trustworthy (Rafalak et al., 2014; Rains & Karmikel, 2009).
Believability of website	*Website believability* is the extent to which a website is accepted or regarded as true, real, and credible (Prat & Madnick, 2008)
Sense of presence with a website	Consumers’ *sense of presence*, also known as a “website’s atmospherics,” is the positive manipulation of design, colour, and graphics of a website (Hunter & Mukerji, 2011).
Website involvement	*Website involvement* is the perceived relevance of the website based on the inherent needs, values, and interests of the consumer (Jiang et al., 2010).
Technology helpfulness	*Technology helpfulness* refers to a technology’s support and ability to provide adequate, effective, and responsive advice that may be necessary to complete a task, including, but not limited to instructions, guidelines, and help pages (AlHogail, 2018).
Purchase intention	*Purchase intention* is the likelihood that consumers will plan or be willing to purchase a certain product or service in the future (Wu et al., 2011).
Usage intention	*Usage intention* is the users’ decision process in which customers decide whether or not to choose and use a product or service (Dehghani, 2018).

2.3 Research Linkage Model

A conceptual framework (Figure 2.1) was developed, based on the synthesised information found in the literature that has been highlighted in the introductory chapter (Chapter 1) and discussed in more depth in this chapter (Chapter 2).

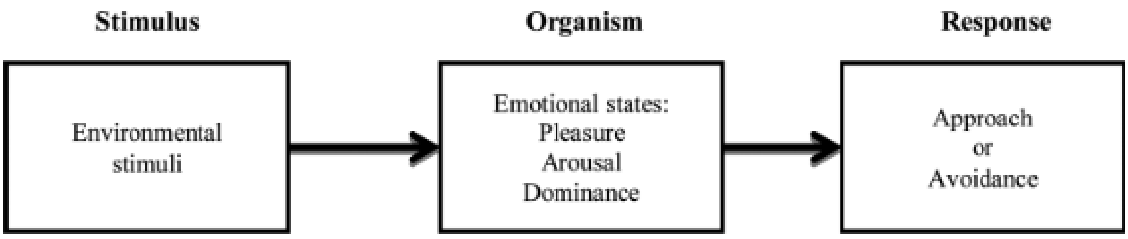
Figure 2.1: *Conceptual Framework*



This model was developed by combining two key frameworks for influencing and understanding technology adoption: these are the SOR framework developed by Mehrabian and Russel (1974) (Figure 2.2) and the TAM developed by David (1985) (Figure 2.3). The framework was created by incorporating SOR's environmental stimuli aspect and TAM's cognitive and behavioural response aspects.

Eight experimental conditions were then developed, based on the manipulation of three independent variables of "purchase type," "AI gender," and "anthropomorphism level." The literature highlighted five cognitive responses that occurred after participants were exposed to an environmental stimulus; the five dependent variables (cognitive responses) were "website credibility," "website believability," "website sense of presence," "website involvement," and "technology helpfulness." The conceptual framework's purpose was to understand how participants' usage and purchase intentions (behavioural responses) were affected by an environmental stimulus and cognitive responses. Next, the literature on the SOR and TAM frameworks are discussed to understand how the combination of the two frameworks were used to understand how participants responded to AI in a marketing and tourism context.

Figure 2.2: *Stimulus Organism Response (S-O-R) Framework*

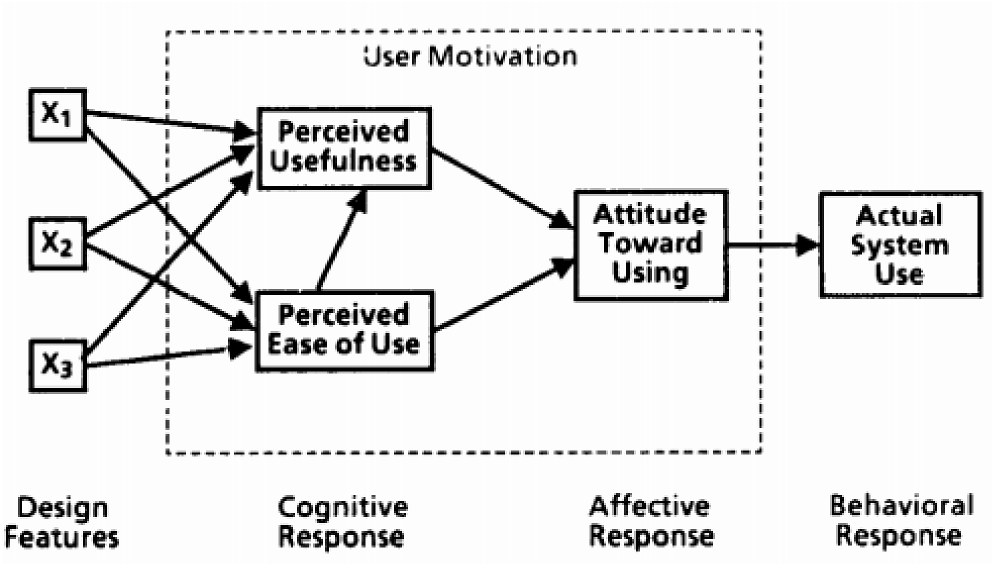


From *An Approach to Environmental Psychology*, by A. Mehrabian and J. Russell, 1974, MIT Press. Copyright 2019 by APA.

The SOR framework presented in Figure 2.2 was developed by Mehrabian and Russell (1974), and used to understand how physical stimuli impact the behavioural responses of individuals, and how the consequent emotional states then influence the extent to which they want to remain in or interact with that environment. This model implies that (S) stimuli lead to a change perception of an (O) organism, which creates a (R) response in the consumer (Perumal et al., 2021). According to this model, when participants are subjected to an environmental stimulus which impacts their emotional perceptions throughout the process, this eventually creates a response, with two possible reactions: approach or avoidance (Perumal et al., 2021). The SOR framework has been used extensively in the marketing (Chopdar & Balakrishnan, 2020; Kim et al., 2020; Suparno, 2020; Zhu et al., 2019), and tourism literature (Ben Haobin et al., 2021; Hunter & Mukerji, 2011), to understand the impact of an environmental stimulus on a consumer's emotions, and how this change in emotions eventually leads to a change in behaviour. Artificial intelligence is an ever-evolving concept (Goyache et al., 2001), so identifying how consumers' purchase and usage intentions could be increased using manipulations of environment stimuli, requires new innovative frameworks to highlight the importance or unimportance of specific stimuli and variables.

In previous use of the SOR framework in a marketing context, the model was used to characterise online stimuli (known as "controlled elements") and their impact on consumers' online behaviour (Gatautis et al., 2016). Factors for successful technology behavioural responses include information quality (usefulness), sensitive content, time, and functionality (ease of use), however, the two key and prominent factors are those of "usefulness" and "usability of technology" (Sarkar & Loureiro, 2013). This explains that in order for consumers' purchase and usage intention in relation to AI technology to occur, the AI must be designed to be both useful and easy to use, to accurately and efficiently fulfil users' wants and needs. The purpose of this research was to create an understanding of the influential factors on usage and purchase intentions that have implications for how AI technology is used for both marketing and tourism purposes, as well as for technology companies developing AI for consumer applications. Therefore, the use of the SOR framework in this study was to combine its environmental stimulus aspect with TAM, as discussed next.

Figure 2.3: *Technology Acceptance Model*



From *A technology acceptance model for empirically testing new end-user information systems*, by F.D. Davis, 1985, *M.I.T Press*. Copyright 2006 by Massachusetts Institute of Technology.

The technology acceptance model was developed to identify the adoption of a technology at the individual level (Davis, 1985). The technology acceptance model identifies perceived usefulness and perceived ease of use as two key cognitive responses that are used to form an attitude towards using the system, which leads to a behavioural response of actual system usage (Davis, 1985; Legris et al., 2003; Porter & Donthu, 2006). The technology acceptance model was developed to understand and explain users' behaviour of technology (Legris et al., 2003). Pavlou and Fygenson's (2006) research highlighted the importance of perceived usefulness and ease of use as salient beliefs for the prediction of e-commerce adoption. The current research combined TAM's cognitive and behavioural response concepts with SOR's environmental stimuli to identify how participants behaved with AI. Users' perceived ease of use response understanding was developed through the inclusion of three dependent variables: website sense of presence (Hunter & Mukerji, 2011), website credibility, and website believability (Lewis, 2009). The understanding of perceived usefulness was determined by including two dependent variables: "website involvement" and "AI helpfulness" (see Sarkar & Loureiro, 2013).

Previous AI literature has noted the necessity of usable technology for influencing consumers' purchase and usage intention when engaging with AI. "The full potential of AI systems to assist users is dependent on creating a usable system that directly fills a real need and fits the user's workflow" (Spaulding et al., 2008, p. 3938). Further discussions of the five dependent variables used to identify participants' cognitive responses can be found in research conducted by Lau (2008). Three user adoption studies were developed by Lau to create an understanding of what is necessary when designing usable AI technologies. The findings showed that the following five elements must be followed: developers must 1) detect failure and fails gracefully; 2) make it easy to edit and update; 3) encourage trust by presenting a usable and understandable model; 4) enable partial automation; and 5) consider the perceived value of automation. This information informs the current study, in emphasising that AI software must be consistently managed to ensure consumers benefit from the helpfulness of the technology, are actively involved, and feel a sense of presence while using AI, which is necessary to improve the system's usability, as "usability is one of the critical barriers to widespread adoption of such systems" (Lau, 2008, p 5).

Furthermore, drivers of repurchase intention and satisfying experience (Chopdar & Balakrishnan, 2020), and perceived ubiquity, were found to have a significant effect on users' purchase impulsiveness, supporting the findings of previous literature (Davis & Sajtos, 2009). This understanding is useful to this study as it demonstrates that a website must fulfil all the desires of a consumer to influence adoption. Desires of website use include the helpfulness of a website (Filieri et al., 2018), how involved a consumer feels while operating a website (Hidayatullah et al., 2020), and consumers' positive sense of presence (Eroglu et al., 2001; Hunter & Mukerji, 2011). Artificial intelligence technology is widely available and used in various industries. All AI software is developed for an intended purpose, and created to be useful and easy to use, to affect a process both efficiently and positively.

The following sections explain this study's conceptual framework, by analysing relevant studies in the literature. Separated into three stages, the framework seeks to first understand the direct effects of the environmental stimuli on participants' behavioural responses. In the second stage of the framework, the effects of the environmental stimuli on participants' cognitive responses are identified, and in the third and final stage of the framework, the effects of participants' cognitive response on their behavioural responses (usage and purchase intentions) are identified. All three stages identify how the effects were discovered and identified within previous literature.

2.4 The Influence of Purchase Type, AI Gender, and Anthropomorphism Levels, on Participants' Behavioural Responses

The purpose of the first stage of the conceptual framework developed for this research (Figure 2.1), was to understand how purchase type, AI gender, and anthropomorphism level can be manipulated to create a direct effect on consumers' purchase and usage intentions. *Purchase intentions* are defined as the likelihood that consumers will plan or be willing to purchase a certain product or service in the future (Wu et al., 2011), and *usage intentions* are defined as a user's decision process in which they choose and use a product or service (Dehghani, 2018). As shown in Figure 2.1, a consumer purchase and usage intention is known as a "behavioural response," The following sections discuss how each independent variable has previously had a direct effect on consumers' purchase and usage intentions.

2.4.1 AI Genders' Direct Effects on Consumers' Behavioural Responses

"Artificial intelligence gender" refers to the gender of the avatar (Zhang et al., 2017). The current research sought to understand how participants responded differently to male and female AI when these were manipulated with two other independent variables (purchase type and anthropomorphism level) to create eight experimental conditions.

Artificial intelligence gender bias is a significant issue in AI development (Wellner, 2020). Research on this topic has highlighted the point that algorithms were never created to be discriminatory, so one suggested reason for bias is that algorithms learn from data sets, and because these data sets reflect our world, algorithms duplicate the world's logic and create these biases on their own (Wellner, 2020). In a similar vein to ethnicity bias, AI technology was never considered to be racist or sexist, however these problems arise, as AI cannot understand context, unlike humans. Artificial intelligence gender has been theorised and found to impact on consumer adoption intention (Tay et al., 2014). Its gender has consistently been found to significantly affect consumers' purchase and usage intentions, and identified as altering the effects of online engagement for both males and females (Morante et al., 2017).

Previous literature has identified the difference in males' and females' behavioural responses according to the gender of the virtual avatar (Hanus & Fox, 2015). It has been identified that males adapt better with male avatars, and females with female avatars. This finding has been confirmed in the literature, as masculine avatars have been reported as less attractive than were feminine avatars, and the majority of people prefer human avatars aligned with their own gender (Nowak & Rauh, 2005). This finding relates to the future research stream suggested by Tay et al. (2014), who stated that gender stereotypes have an effect on consumer adoption of AI, influencing consumers' purchase and usage intention (i.e., behavioural responses). Female AI were found to positively influence participants' positive affective evaluations, perceived behavioural control, and acceptance of female healthcare AI, compared to that of male healthcare AI. However, the inverse was found in security robots, as male AI were found to positively influence response evaluations, perceived behavioural control, and acceptance of male security AI, compared to that of female security AI (Tay et al., 2014).

The effect of AI gender is relatively understudied, so understanding how various aspects of bias and behavioural responses impact AI was important in the current study. Creating an understanding of how both males and females are affected by both AI genders, can give AI developers insights into how AI gender can be manipulated to increase adoption, based on consumer interests and personality traits.

2.4.2 Purchase Types' Direct Effects on Consumers' Behavioural Responses

Purchase type is defined as a consumer's reason to purchase via a website, and can be either a hedonic or utilitarian purchase. An *hedonic purchase* is characterised as an affective and sensory purchasing experience of aesthetic pleasure, which occurs by providing consumers a product or service that entices fantasy fulfilment, perceived freedom, heightened arousal, and enhancement of positive emotions (Alzayat & Lee, 2021). A *utilitarian purchase* is characterised as consumption that is more cognitively driven, instrumental, and properties oriented, and occurs by providing consumers a product or service that is concerned with the functional outcomes derived from the consumption experience (Alzayat & Lee, 2021). This research set out to understand how purchase types interact with other independent variables to affect consumers' purchase and usage intention (i.e., behavioural responses) positively. This section discusses how purchase types (hedonic and utilitarian) have impacted consumer purchase and usage intention as discussed in the literature, to create a theoretical foundation for this research's method and findings.

Through the adoption of the SOR framework, Suparno (2020) investigated the relationships amongst religiosity, shopping value, attitude, and online purchase intention, to create an environmental stimulus to understand its effect on consumers' cognitive and behavioural attitudes, and the resulting impact on users' online purchase intention. The research found that hedonic shopping values and religiosity had a positive and significant effect on all types of attitudes, and these attitudes were found to have a positive effect on online purchasing intention (see Suparno, 2020). This finding is significant, as hedonic purchases often increase users' emotions and result in a higher likelihood of influencing purchase intentions, due to the nature of involvement with an hedonic purchase (Chaudhuri et al., 2010; Zheng et al., 2019).

Both hedonic and utilitarian purchases have been shown to increase participants' purchase intention, with the level of hedonic and utilitarian information value determining the significance of the effect (Kim et al., 2004). The literature states that consumers' purchase intentions on a website are more strongly influenced for hedonic purchases than for utilitarian purchases (Chaudhuri et al., 2010). Zheng et al. (2019) examined how an interpersonal influence, visual appeal, and portability, influence hedonic and utilitarian browsing and their overall impact on consumers' urge to buy impulsively. Their findings showed that hedonic browsing had a direct positive influence on consumers' urge to purchase impulsively, whereas utilitarian browsing did not have a positive influence.

Peng and Kim (2014) adopted the SOR framework to understand consumers' online shopping behaviours. To test hedonic and utilitarian shopping values, environmental stimuli were manipulated to understand the effects on consumers' attitudes to online shopping and emotional purchases, and to identify the effect on their repurchase intentions (see Peng & Kim, 2014). Their findings showed that hedonic shopping had a positive effect on consumers' attitudes, which in turn, were found to significantly affect their online repurchase intentions. Utilitarian shopping values were shown to have no significant relationships with either emotional purchase or repurchase intention (see Li et al., 2020; Peng & Kim, 2014).

This section highlights the effect of predicting users' behavioural responses based on hedonic purchases, when compared to utilitarian purchases, leading to the prediction that a hedonic travel purchase will have a higher likelihood of leading to AI adoption for consumers, compared to that of a utilitarian purchase. However, understanding consumer purchase and usage intention is difficult, as various factors can create an influence. Therefore, this research was interested in understanding how the creation of multiple environmental stimuli influence consumer purchase and usage intention when engaging with AI, when various independent variables are manipulated.

2.4.3 Anthropomorphism Levels' Direct Effects on Consumers' Behavioural Responses

Anthropomorphism is defined as the attribution of distinctively human-like feelings, mental states, and behavioural characteristics to inanimate objects, or animals (Airenti, 2015; Salles et al., 2020). The current research was interested in understanding how high and low levels of anthropomorphised AI influenced consumers' purchase and usage intention, and defining what this influence was, when manipulated with other variables. "Anthropomorphised AI level" refers to the variation of a talking avatar, voice, and other visual aspects of a virtual avatar (Gong, 2008). To understand this effect, the literature discussed in the following section was synthesised to help understand anthropomorphisms' direct effect on users' behavioural responses.

Artificial intelligence continues to be integrated into our daily lives, and the development of AI technology has seen virtual assistants evolve further towards the social realm, becoming more anthropomorphised and viewed less as assistants and more as companions (da Costa, 2018). Numerous studies have noted the importance of future research on AI systems and anthropomorphised levels that are required to influence consumers' purchase and usage intention (Pantano & Pizzi, 2020; Pelau & Ene, 2018). Previous studies have highlighted the effect of anthropomorphism on a brand (Laksmidewi et al., 2017). Researchers found that anthropomorphism on its own does not increase consumers' evaluation of a service, but the inclusion of various other features combined with anthropomorphism can increase consumer adoption, leading to increased purchase and usage intentions. Anthropomorphic behaviour has been shown to affect consumer purchase intention through the mediation of perceived product efficiency (Laksmidewi et al., 2017), informing this research of the necessity of anthropomorphic AI, while ensuring the software is developed to be both useful and usable to influence purchase and usage intention.

Successful anthropomorphic technology requires similar abilities and traits to those of humans, to achieve consumer adoption (Jia et al., 2021). This research theorised that higher levels of anthropomorphism in AI will produce stronger purchase and usage intention than do lower levels of anthropomorphism. This prediction is consistent with a study that found that anthropomorphism of a brand can produce both negative and positive emotions, ultimately affecting consumers' purchase intentions (Tong et al., 2020). In a green brand context, eyes and facial expressions of an anthropomorphic avatar have been found to increase consumer purchase intention. Furthermore, in a chatbot context, anthropomorphism has been shown to impact behaviour and usage intentions based on how human-like the chatbot was perceived (Han, 2021). This research attempted to replicate these finding within an AI travel itinerary context, by understanding the difference in high and low anthropomorphic AI avatars on consumers' behavioural responses.

Based on the literature discussed, it was expected that the manipulation of purchase type and AI gender and anthropomorphism level, will have a significant effect on consumers' behavioural responses. Accordingly, the first hypothesis stream is presented next.

2.4.3 Hypothesis One: Effects of Purchase Type, AI Gender, and Anthropomorphism Levels, on Consumers' Behavioural Responses

Based on the literature discussed in this section, it was expected that the manipulation of purchase type, anthropomorphised level, and AI gender, will have a significant effect on consumers' purchase intentions and intentions to use AI (behavioural responses). This research was interested in understanding how the interaction of these three variables would create eight experimental conditions, to determine how the manipulations directly affect participants' behavioural responses. Therefore, the following hypotheses were proposed:

H1a: Purchase type, and artificial intelligence gender and anthropomorphism level, will have a direct effect on participants' usage intentions.

H1b: Purchase type, and artificial intelligence gender and anthropomorphism level, will have a direct effect on participants' purchase intentions.

2.5 The Influence of Purchase Type, AI Gender, and Anthropomorphism Levels, on Users' Cognitive Responses

The second stage of the conceptual framework (Figure 2.1), is interested in understanding the effects of purchase type, and AI gender and anthropomorphism level on participants' five cognitive responses (i.e., website credibility, website believability, website sense of presence, website involvement and technology helpfulness). This section discusses the effects of the three independent variables on each cognitive response that was identified in the literature.

2.5.1 Purchase Type, Al Gender, and Anthropomorphism Levels' Effects on Consumers' Perceptions of Website Credibility and Believability

Website credibility and believability are important aspects influencing consumers' experiences with websites and technology. *Credibility* is defined as the judgment made by a user about the believability of a website, and the belief that information found on the website is true and trustworthy (Rafalak et al., 2014; Rains & Karmikel, 2009). *Website believability* is defined as the extent to which a website is accepted or regarded as true, real, and credible (Prat & Madnick, 2008). Both aspects are necessary for understanding how consumers perceive a technology; a user's initial perception of the credibility and believability of a website can create both positive and negative responses in the user's mind. Ensuring a website is both credible and believable is of vital importance for ensuring a user has a positive intention to use the website and ultimately create a behavioural response (Janssen et al., 2016). Both cognitive responses are closely aligned; therefore, the two will be discussed in the same vein.

2.5.1.1 Artificial intelligence gender's effects on website credibility and believability

As explained in Section 2.4.1, AI gender is dependent on the gender perceived visually by a user. The literature shows that a participant's gender and the AI gender used on a website or in technology, impacts the users' views on the credibility and believability of the website (Craciun & Moore, 2019). As shown by Tay et al. (2014), gender stereotypes influence participants' views and use of technology, and consumers often judge virtual avatars according to job stereotypes and gender biases surrounding the role they are undertaking. For example, female virtual avatars were found to produce higher adoption intentions when the job they were portraying was in the healthcare sector, whereas male virtual avatars were adopted more readily when portraying a job in the securities sector (Tay et al., 2014). Furthermore, Cranium and Moore (2019) stated that the gender of an online reviewer influenced how credible a participant viewed the online review. Female reviewers were found to harm the credibility and believability of information in participants' views, whereas male reviewers had no effect.

2.5.1.2 Purchase type's effects on website credibility and believability

As explained in Section 2.4.2, purchase types are dependent on a consumer's reason for purchasing, in relation to whether these are to fulfil a hedonic or utilitarian need. Within virtual environments, hedonic purchases have been known to involve different processing styles by participants compared to those used for utilitarian purchases. The difference is that a hedonic purchase requires more sensory based stimuli and must be more imaginative if it is to persuade consumers to develop purchase intentions (Micu & Coulter, 2012). This suggests that the credibility and believability of a website can be affected by the emotions created through the purchase of either a hedonic or utilitarian experience. As previously mentioned, hedonic purchases stimulate a greater emotional connection than do utilitarian purchases (Suparno, 2020), so it is predicted that a hedonic purchase will increase the need for credibility and believability of a website to increase consumers' likelihood of purchasing via that technology. Further proof of this theory can be found in Peng and Kim's (2014) research, in which they identified emotional (hedonic) purchases as having a direct effect on consumers' view of the credibility and believability of a website or review of a website (Guo et al., 2020).

2.5.1.3 Anthropomorphism level's effects on website credibility and believability

The literature has highlighted the positive influence of highly anthropomorphised AI on how a user perceives the credibility and believability of a website. Nowak (2000) argued that the higher the level of anthropomorphism of a virtual agent or avatar, the more a user's believability and credibility perception of the website will increase, compared to a weakly anthropomorphised avatar. However, understanding the differences between high and low levels of anthropomorphism in AI has been widely debated. Yuan and Dennis (2017) suggested that the inclusion of facial features on a non-human object has a greater impact on adoption than does adding life-like human voices. Anthropomorphised avatars have previously been perceived as more attractive, credible, and susceptible to being chosen by a user (Alves & Soares, 2017), implying that the higher the level of anthropomorphism, the more credible users perceive the avatar to be. This finding was consistent with the work of Nowak and Rauh (2005), who identified highly anthropomorphised avatars as being perceived as more credible, believable, and attractive. Based on the findings presented in this section, it is believed that the higher the level of anthropomorphism of an avatar, the greater a user's credibility and believability perceptions will be.

It was therefore theorised that purchase type, and AI gender and anthropomorphism level, will interact to create an indirect effect on participants' views of the credibility and believability of a website. This research attempted to determine this relationship to inform the literature and AI developers of the impact and ideal arrangement of purchase type, and AI gender and anthropomorphism level.

2.5.2 Purchase Type, AI Gender, and Anthropomorphism Levels' Effects on Consumers' Website Sense of Presence

A consumer's sense of presence with a website has been previously found to impact their overall experience (Nowak & Biocca, 2003). Consumers' sense of presence is also known as "website atmospherics," and arises from the positive manipulation of design, colour, and graphics of a website (Hunter & Mukerji, 2011). The purpose of this section is to highlight how website sense of presence has been shown to be affected by purchase type, and AI gender and anthropomorphism level.

2.5.2.1 Artificial intelligence gender's effects on website sense of presence

Virtual avatar genders have been found to affect participants' sense of presence while using technology. Yoon et al. (2015) studied how different types of cognitive styles (object and spatial visualisation) and virtual avatar gender differences affected a user's visual information process and their sense of presence within a virtual environment. Their research found that the moderating role of AI gender had an impact on the relationships between visual cognitive style and sense of presence. Males and females were found to process information differently: "compared with males, females tend to have a better sense of perceiving whole imagery and vividness of colour, shape, texture, or other aspects of objects" (Yoon et al., 2015, p. 8).

Furthermore, studies have shown that a consumer's sense of presence while using a website is a significant factor in understanding their intention to use virtual avatar technologies within a website (Jung, 2011; Venkatesh & Johnson, 2002). This understanding confirms previous findings, in that there is a known variance in visual cognitive ability and preference between genders (Coluccia & Louse, 2004; Cutmore et al., 2000).

2.5.2.2 Purchase type's effects on website sense of presence

Consumers' online atmospherics (also referred to as their "sense of presence") (Hunter & Mukerji, 2011) while using a website, work similarly to atmospherics in a physical retail shop. Atmospherics are part of the total product experience, in that consumer do not just seek to fulfil a need when shopping, but are also looking for a pleasurable experience while purchasing (Kotler, 1973). Consumers desire the same total product experience while shopping online, seeking a well-rounded experience rather than just fulfilling a desire. Yoon et al. (2015) identified hedonic purchases as having a greater impact on consumers' online sense of presence compared to that of utilitarian purchases. This research predicted that a user making a hedonic purchase will have an increased sense of presence, due to the nature of the purpose, involving excitement and pleasure, whereas utilitarian purchases are mundane and do not require as much thought from the user.

2.5.2.3 Anthropomorphism level's effects on website sense of presence

A consumer's sense of presence is a key performance goal for all technology, providing insights into both the software and the user (Schroeder, 2002), by showing how anthropomorphism can increase a user's sense of presence, which is key in determining future AI developers' knowledge. Previously, the level of anthropomorphism was found to influence a user's sense of presence, with higher levels increasing the immersion felt by the user within a virtual environment, influencing their overall experience (Nowak & Biocca, 2003). Sense of presence is required in AI development, as it requires the users to feel as if they were able to perceive the interaction just as they would in a physical shop (Nowak, 2001). This research was interested in confirming the finding that higher levels of anthropomorphic technology results in users' increased sense of presence with the technology.

Based on the literature discussed in this section, it was expected that participants' purchase type, and AI gender and anthropomorphism level, will significantly affect their sense of presence with an AI technology.

2.5.3 Purchase Type, AI Gender, and Anthropomorphism Levels' Effects on Consumers' Website Involvement

Website involvement is defined as the perceived relevance of a website based on the inherent needs, values, and interests of the consumer (Jiang et al., 2010). This section's purpose is to explain how purchase type, and AI gender and anthropomorphism level were previously found to influence users' website involvement.

2.5.3.1 Artificial intelligence gender's effects on website involvement

Artificial intelligence gender has previously been understood to alter the effects of online involvement and engagement in both male and female users (Morante et al., 2017). Males and females react differently, depending on the gender of the virtual avatar they are subjected to (Hanus & Fox, 2015). This explains the need for further research on how males and females differ in their involvement with virtual avatars of the opposite and same gender, while also understanding the comparisons between them. Social rules such as gender, have been argued to impact consumers' involvement with software, as people tend to overuse human social issues such as gender and ethnicity by considering these aspects while interacting with software (Nass & Moon, 2000).

Differences in AI gender have been shown to directly affect consumers' involvement with websites and technology. Female virtual assistants were found to produce significantly higher usage intentions in a customer support context, compared to the effects produced by male virtual assistants (Toader et al., 2020). This finding builds on previous literature that states user adoption and involvement is increased when users are subjected to a female AI and when the technology is used for customer support (Tay et al., 2014). This research builds on these findings to understand how AI gender and consumer involvement with AI are impacted in the context of customer planning activities (i.e., travel itineraries) instead of in customer support.

2.5.3.2 Purchase Type's Effects on Website Involvement

Sarkar and Sarkar (2019) sought to understand the effects of hedonic and utilitarian purchases on participants' continued involvement and use of a technology. The researchers identified two key findings: hedonism involvement is dependent on 1) consumers' surfing task orientation, and 2) the extent to which the technology impacts their imagination, whereas utilitarianism involvement is dependent on the consumers' information-seeking task orientation and the perceived relevance of information (Sarkar & Sarkar, 2019). These findings are consistent with prior research on consumer involvement that explained product involvement is affected by both consumer cognitive and emotional elements (Zaichkowsky, 1985). Involvement has been shown to be a better driver for hedonic purchases than for utilitarian ones (Hollebeek, 2011; Hollebeek et al., 2014). Participant purchase type (hedonic and utilitarian) has been consistently used to understand involvement with a website and the impact of involvement on participants' purchase and usage intention. Further evidence of this is found in a study by Chaudhuri et al. (2010), which showed that hedonic purchases required higher levels of involvement and a longer thought process by users. Hedonic purchases require satisfaction of a service, which ultimately indicates how involved a user is (Chaudhuri et al., 2010).

Building on the findings of purchase types effects on involvement, earlier studies explained that consumers' involvement with a website is affected by cognitive and affective components (Park & Young, 1986). Consumers' cognitive involvement has been found to relate to rational thinking and is considered a utilitarian motive, whereas consumers' affective involvement is related to an emotional or hedonic motive (Park & Young, 1986). Understanding how AI can leverage both purchase types is essential in creating an understanding of how involvement can be improved to increase consumer adoption of AI, for both hedonic and utilitarian products and services.

2.5.3.3 Anthropomorphism level's effects on website involvement

Previous studies have analysed anthropomorphism and its effect on consumer perceptions of a product. For example, Aggarwal and McGill (2007) found that the more human consumers found a product to be, the greater was their involvement and liking of the products. Anthropomorphic advertisements have been shown to influence significantly stronger attitudes and involvement perceptions that do non-anthropomorphic advertisements (Başfirinci & Çilingir, 2015). These findings led to the prediction that the higher the anthropomorphism level of an AI, the more likely the users' behavioural responses will be positively influenced.

Further evidence of this influence within a chatbot context was found in Sivaramakrishnan et al.'s (2007) research. Their study analysed the role of anthropomorphism on a human-like chatbot in an online retail environment. Anthropomorphism was shown to positively impact consumer involvement and purchase intention when the website's static information was limited. One interesting finding that related directly to the current research, was the interaction of anthropomorphism level and purchase type. It was discovered that the use of an anthropomorphic chatbot resulted in a negative impact on purchase intention when consumers were driven by utilitarian consumption (Sivaramakrishnan et al., 2007). The current study built on these findings to understand if a travel itinerary context had an effect on hedonic and utilitarian purchase involvement, and the relation with the anthropomorphism level of the AI.

Based on the literature discussed in this section, it was expected that participants' purchase type, and AI gender and anthropomorphised level, will influence consumer involvement with AI.

2.5.4 Purchase Type, AI Gender, and Anthropomorphism Level's Effects on Consumers' Perceptions of Technology Helpfulness

Technology helpfulness is defined as a technology's support, and ability to provide adequate, effective, and responsive advice that may be necessary to complete a task, including but not limited to instructions, guidelines, and help pages (AlHogail, 2018). This section's purpose is to understand how purchase type, and AI gender and anthropomorphism level were previously found to influence technology helpfulness, and used as a theoretical basis for this research.

2.5.4.1 Artificial intelligence gender's effects on technology helpfulness

Virtual avatar gender in a video game context has been shown to produce significant differences in help-seeking behaviours between male and female avatars (Lehdonvirta et al., 2011; Lehdonvirta et al., 2012). Both Lehdonvirta et al. (2011) and Lehdonvirta et al. (2012), highlighted users' preferences for the helpfulness of female avatars over that of male avatars. This demonstrates that female AI (virtual avatars) are perceived as more helpful due to gender-based stereotypes, as confirmed by Tay et al. (2014). The current study built on this discovery to determine if the same stereotypical views transferred to a travel itinerary website context. This would help understand how AI can be developed for different contexts to increase purchase and usage intentions of a product or service through AI (see Chiu et al., 2005). Chiu et al.'s (2005) research suggests that applying interactive virtual reality and visual effects will efficiently and successfully stimulate positive attitudes while increasing consumers' perception of website helpfulness.

Although a significant result was found in a video game context, Shang et al. (2019) identified no significant gender impact from AI on perceived website helpfulness. Although this finding suggests several possible explanations, the current study was focused on identifying how the manipulation of purchase type, and AI gender and anthropomorphised level, could come together to affect user perceptions of website helpfulness.

2.5.4.2 Purchase type's effects on technology helpfulness

Understanding the role of technology helpfulness on consumers' online search experiences is vital, to gain knowledge of what is important for consumers when purchasing online (Sun & Spears, 2012). Sun and Spears (2012) identified the effect of hedonic and utilitarian searches on consumers' attitudes to website helpfulness and effectiveness, which were moderated by the levels of frustration felt by consumers. Hedonic and utilitarian purchase type helpfulness was previously portrayed differently within an OWOM (online word-of-mouth) context. It was discovered that utilitarian purchase information is perceived as more helpful when the action of the service is explained, whereas hedonic purchase information is perceived as more helpful when the reaction to the service is explained (Moore, 2015). The helpfulness of technology positively influences participants' experiences of a website, for both hedonic and utilitarian purchases. This occurs because information is required for both necessities as well as pleasurable purchases. Therefore, this research attempted to understand how hedonic and utilitarian purchases affect users' technology helpfulness.

2.5.4.3 Anthropomorphism level's effects on technology helpfulness

The helpfulness of a robot has been found to influence the emotional aspects of technology (Gonsior et al., 2012). Different levels of anthropomorphism create a more emotional robot through facial features and visual and audio cues, impacting its emotional aspect. The current research attempted to build on this finding to understand how different levels of anthropomorphised AI have a significant impact on website helpfulness. This predicted finding is supported by the work of Kühnlenz et al. (2013), who confirmed that the emotional aspects of a robot did have a significant effect on helpfulness. Kääriä (2017) built on this finding by explaining that the anthropomorphism level of AI significantly influenced consumers' perceived helpfulness, usefulness, and ease of use of the website. These aspects relate directly to Davis (1985)'s TAM model, which highlights usefulness and ease of use of technology as important factors of successful technology.

Waytz et al.'s (2014) findings identified that the higher the level of anthropomorphism of technology, the more likely it is that users will perceive the technology as helpful and useful for completing their tasks. However, higher levels of anthropomorphism have been shown to increase how accountable a technology is perceived as by a user, indicating that determining the optimal level of anthropomorphism in AI will enable an understanding of how anthropomorphism impacts and affects technology helpfulness.

Based on the literature discussed, it was expected that the manipulation of purchase type and AI gender and anthropomorphism level, will have a significant effect on consumers' perceived helpfulness of AI.

Accordingly, the second hypothesis stream is presented next.

2.5.5 Hypothesis Two: Effects of Purchase Type, AI Gender, and Anthropomorphism Levels, on Participants' Cognitive Responses

Based on the literature discussed in this section, it was expected that the manipulation of purchase type, and AI gender and anthropomorphism level, will have a significant effect on the cognitive response aspects of this study. This research was interested in understanding how the interaction of these three independent variables would create eight experimental conditions, and the overall effect this had on the five cognitive responses (website credibility, website believability, website sense of presence, website involvement, and technology helpfulness) to understand how the manipulations affected participants. Therefore, the following hypotheses were proposed:

H2a: Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' website credibility response.

H2b: Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' website believability response.

H2c: Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' website sense of presence response.

H2d: Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' website involvement response.

H2e: Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' technology helpfulness response.

2.6 The Influence of Cognitive Response on Consumers' Behavioural Reponses

The last stage of the conceptual framework (Figure 2.1) sought to identify the effect of the five cognitive responses (website credibility, website believability, website sense of presence, website involvement and technology helpfulness) on users' usage and purchase intentions (behavioural responses).

2.6.1 Website Credibility and Believability Effects on Participants' Behavioural Responses

Participants' views on website credibility and believability were shown to influence users' attitudes towards the study (Lewis, 2009). Participants were shown to have positive interactions with technology when they were positively immersed within a virtual environment (Janssen et al., 2016), and participant immersion in experimental research was also shown to directly influence their views on the believability and credibility of the experiment (Zha et al., 2018). Measuring a participant's view of the credibility and believability of a virtual environment enables an understanding of how these two factors influence participants' purchase and usage intentions within experimental research (Janssen et al., 2016).

Therefore, the credibility and believability of a website increases a participant's purchase intention by creating real emotions about a purchase. To research consumers' views on the credibility and believability of a website, validity checks can be utilised. Palazon and Delgado-Ballester (2013) suggested using validity checks to ensure how consumers are observing the subject of the research, for example, by asking questions about what sort of product they believed they saw (hedonic or utilitarian) and how believable and credible the website felt. Understanding participants' views on the credibility and believability of a website can grant researchers significant insights into how consumers' purchase intention is affected, dependent on whether they are purchasing a utilitarian or hedonic product or service (Chakraborty, 2019).

It is theorised that a participant's view of the credibility and believability of a website may provide an in-depth understanding of participant purchase intention of a technology. Therefore, this research attempted to understand the impact of website credibility and believability on participants' usage and purchase intentions.

2.6.2 Website Sense of Presence Effects on Participants' Behavioural Responses

Hunter and Mukerji (2011) suggested that when a consumer does not feel a sense of presence while using a website due to the online atmosphere, the consumer's requirements and buying goals will be negatively affected and eventually impact on their purchase intentions and overall experience of the website. However, when online atmospherics influence and increase a consumer's sense of presence, the website gains the power to facilitate purchase intentions, increasing consumer browsing and shopping times (Eroglu et al., 2001; Hunter & Mukerji, 2011). The purpose of strong user sense of presence is to ensure the design on a website incorporates the visual aspects of design, colour, and graphics. Ensuring these aspects are appropriately designed, consumers' intention to stay, explore and affiliate with the software is increased (Hunter & Mukerji, 2011), eventually leading to increased purchase and usage intentions. This finding is applicable not just to an online context, but to a tourism context as well, as a hotel's servicescapes (sense of presence) have been shown to influence hotel guests' experiences. It was discovered that a consumer's positive experience with hotel decor leads to an approach response, whereas a negative experience leads to an avoidance response (Bitner, 1992).

Further evidence of the importance of measuring online atmospherics and a consumer's sense of presence to identify their adoption intentions online and in a tourism context was provided by Choi and Kandampully (2019). These researchers' objective was to "identify some of the atmosphere elements within a hotel that might enable customers to better engage with the hotel" (p. 1). To test this, they utilised the SOR framework; four stimuli were examined: social, public design, room design and the ambience of a hotel. These stimuli were manipulated to participants to assess their impacts on customer satisfaction. This manipulation was tested to understand hotel guests' willingness to suggest and discuss the hotel with others through WOM recommendations (Choi & Kandampully, 2019). Their findings confirmed room design and social aspects as significant antecedents impacting consumers' satisfaction, intention to spread positive WOM recommendations, and their repurchase intentions.

Furthermore, the greater a consumer's sense of presence within a virtual environment, the greater their consumer satisfaction, and purchase and usage intention will be within the virtual environment (Yoon et al., 2015). A consumer's positive sense of presence was previously shown to interact with and positively affect consumers' involvement, which in turn led to strong purchasing intention (Fortin & Dholakia, 2005).

Overall, it was predicted that the greater a participant's sense of presence, the more positively their purchase intention would be. Understanding a participant's sense of presence while using a website can give researchers valuable information to understand the effect it had on their purchase intention, much like the effects of atmospherics in a physical retail shop (Nowak, 2001). If consumers are present while browsing a website they are paying much closer attention, taking in all aspects of the website (e.g., design, usability, and usefulness) that influence their purchase intentions.

2.6.3 Website Involvement Effects on Participants' Behavioural Responses

Involvement with a website has been shown to positively affect consumers' purchase and usage intentions (Hidayatullah et al., 2020), but the extent of the influence is still relatively unclear. Therefore, this study attempted to understand the influences of consumers' interactions with a website, and the effect these have on purchase and usage intentions.

Hepola et al. (2020) found participant involvement positively influenced their continued use intentions with a website. Their results showed that involvement and engagement were stronger drivers of website continuance than was satisfaction, when consumers were purchasing for hedonic reasons (Hepola et al., 2020). However, it was found that consumers' interests and attitudes towards a website influenced their consumption and satisfaction, which overall, was a stronger driver of continued use of a website than was engagement when the purchase was for utilitarian reasons (Hepola et al., 2020). Furthermore, the perceived flow of a website was to increase consumers' involvement, engagement, interest, and attitudes towards revisiting and spending time on a website (Hidayatullah et al., 2020; Mathwick & Rigdon, 2004; Wilcox et al., 2011). Research has confirmed consumers' online involvement and engagement and been shown to influence consumers' intention to purchase in an online setting (Fortin & Dholakia, 2005; Valentini et al., 2018). Furthermore, successful user involvement was found to increase user satisfaction, leading to adoption (Carroll, 1997; Dirican & Göktürk, 2011; Hudlicka, 2003).

Involvement of technology for both genders is vital for understanding their eventual purchase intentions. Women require involvement with a website and positive WOM to reduce their perceived risk, whereas men solely require involvement with a website to reduce their perceived risk of use. This difference confirms findings in the literature, that suggest men and women handle, perceive, and relate to new technologies differently (Turkle, 2005). Garbarino and Stahilevitz (2004) studied the relationship between gender and perceived risk levels based on participants' involvement with a website. The researchers found men and women differ significantly in their perceptions of the risks associated with online shopping, depending on whether they received a recommendation or had already engaged with the technology. This finding identified female consumers as having less purchase experience and involvement with a website, which was shown to lead to higher levels of perceived risk (Garbarino & Strahilevitz, 2004). This finding further extends understandings from previous studies, on the known impact of gender on the perceived risks of online shopping: women were found to perceive a higher level of risk for online purchasing compared to that of men (Chang & Chin, 2010; Flynn et al., 1994; Hersch, 1996), and positive WOM had a strong influence on women but none on men (Chang & Chin, 2010).

Virtual reality (VR) tourism is a revolutionary marketing tool that has recently arisen from the fourth industrial revolution. This technology gives tourism retailers the capability of showing consumers their potential destination before they confirm their travel plans (Kim et al., 2020). Kim et al. (2020) sought to understand the key factors of VR tourism's purchase intention by adopting the SOR framework. Researchers tested how a consumer's involvement with an authentic experience affected their cognitive and behavioural responses, and the effect this had on their intention to visit a destination. The results demonstrated that a "consumer's intention to visit the destination shown in the VR tourism content was influenced by their attachment to VR tourism experiences" (Kim et al., 2020, p. 83-84). Furthermore, the results also showed that consumers' authentic experience with VR tourism was a key factor in the commercialisation of VR (Kim et al., 2020). These findings highlight that consumer involvement with a technology positively influences their purchase and usage intentions.

2.6.4 Technology Helpfulness Effects on Participants' Behavioural Responses

The literature has identified website helpfulness as an important characteristic affecting consumers' purchase and usage intention. Human-computer interaction software design should be fluid, pragmatic, and focus on human factors such as providing a useful, usable, and helpful service (Bannon, 1995). An increase in users behavioural intentions occur because the less frustrating and more helpful the information on a website is, the more likely consumer purchase and usage intention will be positively affected (Filieri et al., 2018). Technology helpfulness is a key component of a successful and adoptable website, and the helpfulness of a technology was shown to increase consumers' purchasing behaviour regardless of how they rated their experience with the website (Lee et al., 2017). However, higher levels of anthropomorphism have been shown to increase how accountable a technology is perceived to be by users. Determining the optimal level of anthropomorphism in AI would allow for the determination of its impact on technology helpfulness, and therefore, its influence on users' purchase and usage intentions (Waytz et al., 2014).

Understanding users' perceptions of the helpfulness of a website has shown to be vital for website developers wanting to increase consumers' online purchasing intention for both males and females. Chiu et al. (2005) identified several important insights into technology helpfulness and its role in consumer adoption of a website. Firstly, male consumers were found to be strongly value and goal orientated when using a website; the greater the usefulness and helpfulness of a technology, the greater was the users' purchase intention. Secondly, females were found to be more sensitive than males towards online purchasing intentions and attitudes: "an online store that is perceived by females as user-friendly will facilitate online store visits and online purchase intentions more than other online stores that are seen as difficult to shop in" (Chiu et al., 2005, p. 30). Furthermore, the greater the helpfulness of a website or website review, the more favourably both males and females will evaluate the website. Inversely, lower levels of helpfulness of a website or website review mean consumers' decision making becomes more difficult, due to ambivalent feelings towards the website (Ghosh, 2018).

Liao et al. (2020) discovered that the helpfulness, usability, and usefulness of a website were essential criteria for influencing positive consumer usage while using new software. This finding in relation to usability and usefulness affecting purchase and usage intention, directly relates to Davis (1985)'s TAM model, one of the two conceptual models this research was based on. The current research allows for an understanding of how AI can be developed for different contexts to increase purchase and AI usage intention.

Based on the findings in this section, the following hypotheses were proposed. These hypotheses reflected the need to understand the effects of users' cognitive responses on their behavioural responses (purchase and usage intentions).

2.6.5 Hypothesis Three: Effects of Cognitive Responses on Participants' Behavioural Responses

Based on the literature discussed in this section, it was expected that the five cognitive response aspects presented in Figure 2.1 will have a significant effect on users' behavioural responses. This research was interested in understanding how website credibility, website believability, website sense of presence, and website involvement and technology helpfulness, affect participants' usage and purchase intentions. Therefore, the following hypotheses were proposed:

H3a: Website credibility response will have an effect on participants' AI usage intention, and purchase intention.

H3b: Website believability response will have an effect on participants' AI usage intention, and purchase intention.

H3c: Website sense of presence response will have an effect on participants' AI usage intention, and purchase intention.

H3d: Website involvement response will have an effect on participants' AI usage intention, and purchase intention.

H3e: Technology helpfulness response will have an effect on participants' AI usage intention, and purchase intention.

2.7 Control Variable (Users' Overall Mood)

The control variable of users' overall mood will be measured at the beginning of the experiment, to identify how a user's initial mood influenced their overall reaction to the environmental stimuli and their behavioural responses.

Both positive and negative moods can have a wide variety of effects on consumers' decision making; negative moods often result in consumers' thinking negatively about stimuli they are exposed to, whereas positive moods cause consumers to think positively about the stimuli (Schmid & Mast, 2010). This information makes understanding consumers' mood at the time of an experiment crucial for developing a strong understanding of true emotions in relation to a stimulus, which is important, as understanding the effect of moods will allow researchers to identify and comprehensively analyse the way consumer adoption is influenced. Indeed, "moods can influence how people interpret and appraise the events of their lives" (Gray et al., 2001, p. 28).

The Brief Mood Introspection Scale (BMIS) was developed by Mayer and Gaschke (1998) to create an understanding of an individual's current mood state. Mood was found to have a pervasive effort on cognition when individuals show changes in perception, attention, and memory and executive functions, and a sad mood was also found to affect memory for emotional words and facial emotion recognition in consumers (Chepenik et al., 2007). Positive moods often prevail over negative memories, causing people to demonstrate classic mechanisms shown in prior work to influence well-being, but when negative moods prevail over positive memories, the memories can become negatively tainted (Konrad et al., 2016). Schmid and Mast (2010) explained that sad moods resulted in general performance decreases in emotion recognition and produce a better recognition of sad facial expressions than of happy expressions. They also noted that insufficient research has been conducted on the influence of happy moods on emotion recognition. Emotion and mood were found by them to be distinct phenomena in terms of how they were manifested in phenomena experience, which ultimately influenced how mood and emotion impacted on behaviours (Beedie et al., 2005). Furthermore, an individual's emotional state can negatively and positively affect their ability to carry out a job (Hossain et al., 2014). It is for this reason, that participants' overall mood was recorded prior to conducting this study, to understand how their overall mood positively or negatively affected their ability to recognise stimuli, which would alter their responses in the experiment.

2.8 Chapter Summary

This chapter provided a theoretical background to the key areas of interest for this research. The chapter initially presented the key constructs of the research, which were followed by a presentation of the conceptual framework of the study, and an explanation of the combination of the SOR framework and TAM. The chapter was divided into three major sections to explain the three hypothesis streams of the research; the hypotheses were presented at the conclusion of each section. The first section (2.4) explained the first stream of hypotheses, on understanding the direct effects of purchase type, AI gender, and anthropomorphism level on users' usage and purchase intention (behavioural responses). The second section (2.5) explained the effects of purchase type, AI gender, and anthropomorphism level on the five cognitive responses (i.e., website credibility, website believability, website sense of presence, website involvement. and technology helpfulness). The last section (2.6) explained the five cognitive responses' effects on users' usage and purchase intentions (behavioural responses). The final section (2.7) on the control variable, (users overall mood) was provided to identify its use in this research. The following chapters present the development of the experimental stimuli, to understand how the experimental design was created to test the hypotheses presented in this chapter.

Chapter 3. Methodology

3.1 Introduction

This chapter presents the methodology used to understand consumers' cognitive and behavioural responses to AI technology, to test the hypotheses outlined in Chapter 2. A 2 x 2 x 2 (AI gender: male vs female; purchase type: hedonic vs utilitarian; and anthropomorphised level of AI: low vs high) between-subject factorial design was conducted using an online quantitative survey. Purchase type, AI gender, and anthropomorphism level were manipulated as independent variables to create eight unique experimental conditions. These three independent variables were manipulated to test their direct effects on consumers' usage and purchase intentions (behavioural responses) in relation to AI, and the effects on participants' cognitive responses. A pre-test was conducted to test the video configuration, scenario planning, and to ensure the measurement scales used resulted in statistically significant results. Participants were recruited using Amazon Mechanical Turk's online workforce, a revolutionary tool with the potential to transform behavioural research, with the ability to run experiments with a large number of participants (Crump et al., 2013).

3.2 Research Design

Individuals' online purchase type (i.e., their reason for purchasing via a website) was separated into two classifications (see Table 1.2). The first was for *hedonic purchases* characterised as affective and sensory purchasing experiences of aesthetic pleasure, providing consumers a product or service that entices fantasy fulfilment, perceived freedom, heightened arousal, and enhancement of positive emotions (Alzayat & Lee, 2021). The second classification was for *utilitarian purchases*, characterised as consumption experiences that are more cognitively driven, instrumental, and properties oriented, and providing consumers a product or service that is concerned with the functional outcomes derived from the consumption experience (Alzayat & Lee, 2021).

Two scenarios were created to ensure participants were aware of the different manipulations they were subjected to; these were given to participants before they were shown any manipulations. The hedonic scenario was a personalised domestic holiday in the United States of America (USA), and the utilitarian scenario was a personalised domestic business trip in the United States of America (USA). The United States of America was used as the context for several reasons: first was the travel limitations that occurred during December 2020 due to COVID-19, and second was the ability to limit the sample to only include USA participants. It was for these reasons that holiday and business travel within the USA was chosen as the context of this study.

Artificial intelligence gender has been discussed in the literature as having an impact on consumer response and adoption with AI, due to various gender and personality stereotypes (Tay et al., 2014; Wirtz et al., 2018). For this reason, this research studied both male and female AI to understand which gender impacted participants' behavioural responses the most. To emphasise this difference, two AI were created, of different genders (Jane and John), and the voices used were clearly gendered as male and female. The avatars moved in a life-like fashion, but it was clear to participants that they were anthropomorphised avatars; the avatars are presented in Figures 3.1 and 3.2.

Figure 3.1: *Male (John) AI Gender with High Anthropomorphism Level in Visual Representation*

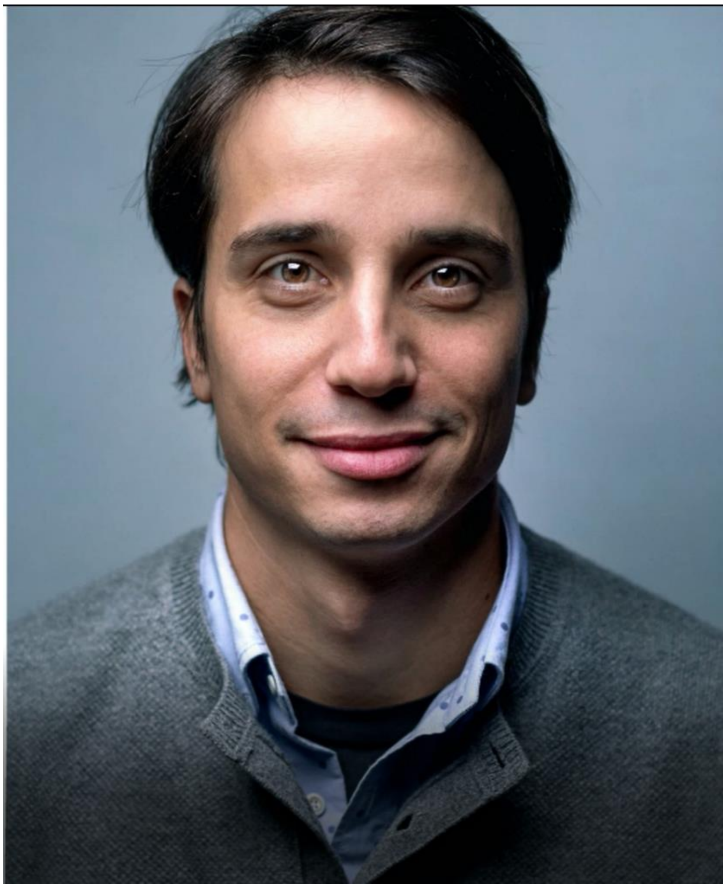


Figure 3.2: *Female (Jane) AI Gender with High Anthropomorphism Level in Visual Representation*

The anthropomorphism level of AI is characterised as the variation of the virtual avatar, voice, and other visual aspects of the technology (Gong, 2008). Anthropomorphism levels have been shown to impact a consumer's behavioural response to technology (Benbasat, 2010; Sheehan, 2018; Wirtz et al., 2018). However, creating an understanding of the optimal level of an avatar's humanoid appearance is still needed (Wirtz et al., 2018).

To create an understanding of the optimal anthropomorphised level of AI, two levels of anthropomorphised AI were developed. These two levels were characterised as "low" and "high" anthropomorphism levels. The differences in manipulations are presented in Figures 3.1 and 3.2. High anthropomorphism levels (Figures 3.1 and 3.2) subjected participants to a life-like avatar with moving facial expressions and projected human emotions, whereas the low anthropomorphised level (Figure 3.3) subjected participants to a moving audio bar.

Figure 3.3: *Low Anthropomorphism Level Visual Form*

The manipulation of purchase type, AI gender, and anthropomorphism level was undertaken to create eight experimental conditions, which were then used to determine direct effects on participants' usage and purchase intentions (behavioural response). Furthermore, the environmental stimuli were used to understand the effects on participants' cognitive responses, and how the cognitive responses affected participants' behavioural responses towards Ryan's Travel's AI website.

3.3 Selection of Artificial Intelligence Context

Artificial intelligence is separated into three major types: supervised learning (SL), unsupervised learning (UL), and reinforcement learning (RL) (Mutiara, 2018). This research used SL as the basic AI type to understand consumer behavioural responses. An SL algorithm operates by utilising and analysing previous "data and feedback from humans to learn the relationship of given inputs to given outputs" (Mutiara, 2018, p.2). The purpose of SL is to analyse input data from a user, to accurately interpret and make suggestions in the form of an output variable. Supervised learning is the most commonly used AI type for chatbots; therefore, this research attempted to create its own version of a chatbot, by building on previous AI concepts that used SL to create personalised travel itineraries (Utrip, 2014). This was undertaken to understand how tourism AI can be manipulated to create a more adoptable and usable service for future users.

The tourism context allowed for the manipulation of multiple purchase types to be distinctly separate for participants. Two purchase types were created: a personalised holiday itinerary (hedonic purchase), and a personalised business trip itinerary (utilitarian purchase). Both purchase types had unique inputs that were required to create a unique itinerary designed specifically for each individual user (outputs). Tourism AI also enabled this study to determine how industry stereotypes affected adoption, based on AI gender. Building on the findings of Tay et al. (2014), context specific stereotypes were shown to influence the adoption of an AI, suggesting that informative AI had a better chance of adoption when male, whereas healthcare or protective AI had a higher chance of adoption when female.

Tourism was chosen as the context for this study due to the ease of setting up and manipulating the technology to be credible and believable in the views of participants. Supervised learning technology is relatively simple to create compared to that of other AI (unsupervised learning and machine learning). The technology operated by asking for a finite set of inputs, such as information on budget, interests, length of stay, location, and commitments. After the technology had interpreted an individual's responses, the software scanned thousands of previous documents and information found online to create a personalised itinerary specifically designed for that individual. Tourism AI allowed this research to create a real-life experience for an individual with the responses at the researcher's disposal. It is for this reason that a tourism context was selected for this research.

3.4 Experimental Design

This research created a 2 x 2 x 2 between-subjects factorial design, to test the effects of three independent variables of "purchase type" (hedonic and utilitarian), "AI gender" (male and female), and "anthropomorphism level" (low and high) on participants' usage and purchase intention (behavioural response). "Purchase type," "AI gender," and "anthropomorphism level," were manipulated to create eight unique experimental conditions (see Table 3.1).

Table 3.1: *Environmental Stimuli*

AI Gender	**Purchase Type**	**Anthropomorphism Level**	
		Low Anthropomorphism (No avatar)	**High Anthropomorphism (Human avatar)**
Male	**Hedonic**	Condition 1	Condition 5
	Utilitarian	Condition 2	Condition 6
Female	**Hedonic**	Condition 3	Condition 7
	Utilitarian	Condition 4	Condition 8

Condition 1: Male, hedonic purchase type, low anthropomorphism
Condition 2: Male, utilitarian purchase type, low anthropomorphism
Condition 3: Female, hedonic purchase type, low anthropomorphism
Condition 4: Female, utilitarian purchase type, low anthropomorphism
Condition 5: Male, hedonic purchase type, high anthropomorphism
Condition 6: Male, utilitarian purchase type, high anthropomorphism
Condition 7: Female, hedonic purchase type, high anthropomorphism
Condition 8: Female, utilitarian purchase type, high anthropomorphism

3.5 Stimuli Development

3.5.1 Creation of Ryan's Travel

The fictitious brand "Ryan's Travel," was created on a website developed for this research to create eight experimental conditions, to ensure participants' prior brand knowledge was not a key factor driving their behavioural responses. Brand awareness has been shown to be an important factor for influencing purchase decisions (Macdonald & Sharp, 2000; X.G. Ji, 2009), therefore, ensuring each participant begins the experiment with the same amount of knowledge was of vital importance. Eight separate conditions were created to understand the effect of the interactions that purchase type, AI gender, and anthropomorphism level had on consumers' perceptions of AI, and the direct effect on their behavioural response. The creation of Ryan's Travel's AI was undertaken using eight videos (Appendix B), to showcase how supervised learning AI interprets inputs from a user, and transforms them into personalised outputs specifically designed for the users. The AI videos were done in three stages.

First, the Ryan's Travel website was created using Wix, a free website development software package. Three pages were created: a home page (Appendix C), a personalised business trip page (Appendix D), and a personalised holiday page (Appendix E). The personalised business trip and personalised holiday pages had specific preferences (inputs) that aligned with each type of travel. Each input question was either phrased as an open-ended question to ensure all requirements of the trip were met, or as a multi choice question to obtain a basic idea of the individuals' wants and needs. Inputs for each webpage are presented in Table 3.2.

Table 3.2: *Business and Holiday Itinerary Inputs*

Holiday Itinerary Inputs	Business Trip Itinerary Inputs
Where are you flying from? (open-ended) What location would you like to go to? (5 options) Trip budget (5 options) Length of stay (5 options) Number of travellers (5 options) Pace of trip (5 options) Adventure activities (7 options) History and art activities (9 options) Entertainment activities (7 options) Shopping (6 options) Rest and recreation (5 options) Cuisine (7 options) Eating out frequency (5 options)	Where are you flying from? (open-ended) What location would you like to go to? (opened ended) Hotel rating (5 options) Length of stay (opened ended) Number of travellers (5 options) Business hours per day (open-ended) Sport activities (6 options) Entertainment activities (9 options) Cuisine (7 options) Eating out frequency (5 options)

The creation of the Ryan's Travel website was necessary to produce the visual content for each condition video, so participants could have a clear understanding of what the AI required to create a personalised business trip/holiday itinerary for them. The second stage followed the creation of Ryan's Travel itineraries. The two itineraries were created, one outlining a personalised holiday based on the preferences selected in the hedonic stimulus, and the other outlining a personalised business trip based on the preferences selected in the utilitarian stimulus.

Lastly, after the creation of Ryan's Travel and itineraries, both input pages were screen-recorded to ensure all conditions were identical apart from the manipulations of each environmental stimulus. This was done for the female and male audio that participants were subjected to. Audio was recorded using Woord's software; a hedonic (holiday) and utilitarian (business trip) script was recorded for both genders (male and female). Each speech was identical apart from the hedonic and utilitarian inputs, presented in Table 3.2. Next, the anthropomorphism level was manipulated. Using CrazyTalk8's software, the high level of anthropomorphised AI was created. This software allowed for the development of a life-like talking avatar (Figure 3.1 and 3.2) that displayed realistic emotions. For the creation of the low level of anthropomorphised AI, a simple audio box was used (Figure 3.3) which created two vastly different manipulations. Lastly, all independent variable manipulations were brought together, and using Corel's Video Studio (video editing software), all variables were manipulated to create eight unique experimental conditions. All eight condition videos are presented in Appendix B.

3.5.2 Justification for Utilising Videos to Demonstrate Ryan's Travel's AI

Previous literature has attested to the usability of videos in experimental research, and evolving technology research has often required videos to create a life-like representation of a technology's capabilities. Technologies such as robotic hotel servers (Chan & Tung, 2019), and 360 degree video journalism (Van Damme et al., 2019), have used videos to demonstrate the technology to participants in experimental design. Heath and Luff (2018) explained that video recording is critical in exploratory experimental research that is designed to outline particular phenomena and expose participants to specific manipulations clearly and concisely. Video recordings were the chosen method of environmental stimuli for this research, as videos were the best way to depict the abilities of AI and SL accurately and correctly for participants. Supervised learning, the most basic form of AI used by Ryan's Travel, operated by receiving labelled inputs (Table 3.2), which were analysed and transformed into specific outputs (travel itineraries presented in Appendices F and G) (Mutiara, 2018). This process would be impossible to explain through other stimuli with the resources available for this study, such as with print advertisements, pictures, or in written form. Therefore, video recordings in conjunction with informative scenarios, had to be used to reduce confusion amongst participants and create a clear and even manipulation of independent and control variables.

3.5.3 Determining Levels and Manipulation of Purchase Type, AI Gender, and Anthropomorphism Level

This research tested the effects of both male and female stereotypes on adoption, guided by the work of Tay et al. (2014). These researchers found that participants accepted social robots more easily when the gender of the robot corresponded with its occupational stereotype, and noted that future research was needed in a field setting, on other types of social robots (chatbots). Therefore, this research studied users' responses to both male and female avatars in a tourism context, to understand if tourism agency stereotypes had an impact on consumers' overall perceptions of AI and eventual adoption of tourism AI. The manipulation of gender was achieved by creating clear visual and audio cues, and through accurate labelling of the AI’s name (i.e., the female was Jane, and the male was John) to inform participants of the AI’s gender. To ensure manipulations were perceived as intended, participants were given manipulation check questions immediately after being exposed to their condition video, to check that they had understood the information correctly.

Next, determining the levels of manipulation for each purchase type was decided by creating two scenarios: one about a domestic business trip, and one about a domestic holiday in the USA. Domestic trips were chosen for this study, as the sample was made up of USA participants. Therefore, to ensure both scenarios were accurate for each individual, a domestic USA trip was chosen as the topic of this experiment. The selection of manipulations was set up by creating a hedonic (luxury) and utilitarian (necessity) service for purchase. Previous literature has identified a business trip as fulfilling a utilitarian purchase goal, and a holiday as fulfilling a hedonic purchase goal (Kronrod & Danziger, 2013). The manipulation of purchase types was created by the AI explaining to each participant their own purchase intentions, using scenarios. Each scenario explained why they were using Ryan’s Travel and what they were intending to purchase. Manipulation checks were then used to ensure participants had understood the information correctly throughout their experience with AI.

Lastly, two levels of anthropomorphised AI were created to understand participants’ response towards AI based on their behavioural responses. Two types of AI were created using two types of visual cues. The highly anthropomorphised AI conditions were created using Reallusion (www.reallusion.com), software that creates real life talking avatars (Figure 3.1 and 3.2) to create a sense of high anthropomorphism for participants. The low anthropomorphised AI conditions were created and represented using an audio bar (Figure 3.3), which provided participants the understanding that the AI was very robotic and was solely there to complete a task rather than create a human connection. All conditions used the same audio recording, to ensure that the only anthropomorphised change was the visual aesthetic of the AI, rather than any other sensory aesthetics.

3.6 Questionnaire Development

3.6.1 Measures for Independent Variables

3.6.1.1 Artificial intelligence gender manipulation check questionnaire items

The literature has utilised many different means of measuring gender manipulation in experimental research. This study adapted the scale developed by McAleer et al. (2014) which was used to obtain participants' views on the gender-based on voices. McAleer et al. (2014) asked participants to rate multiple gender trait items based on a voice they were subjected to; the researchers noted that an alpha greater than 0.85 was considered high. To study the effects of voice on participants in this research, McAleer et al.'s (2014) scale was adapted; four items were used on a seven-point Likert scale ranging from "strongly disagree" to "strongly agree" (see Table 3.3). This scale was used as a manipulation check to ensure participants accurately understood the differences in AI gender under all eight conditions.

Table 3.3: *Likert Items of AI Gender Manipulation Check Scale*

AI Gender Manipulation Check (AIG)	
Coding:	Likert items (strongly disagree/strongly agree)
Q2_AIGa	I considered the AI to be masculine
Q2_AIGb	I considered the AI to be feminine
Q2_AIGc	The voice I experienced on the website sounded like a male voice
Q2_AIGd	The voice I experienced on the website sounded like a female voice

3.6.1.2 Purchase type questionnaire items

The manipulation checks used for hedonic vs. utilitarian purchase type involved two separate scales. The first, presented in Table 3.4, measured participants' views on a hedonic purchase (holiday itinerary) on a two item seven-point Likert scale designed to ensure participants understood the purpose of the AI website (Ryan's Travel). The two items asked participants to rate whether the stimuli they had just viewed were about planning a pleasurable experience and achieving work related goal. The second scale (see Table 3.5), measured participants' views on how hedonic the experience felt on a six item seven-point semantic-differential scale. This scale was adapted from Hepola et al.'s (2020) work; the use of this scale in their research resulted in a Cronbach's alpha coefficient of 0.93 (Hepola et al., 2020). The scale measured participants' views from: not fun/fun, dull/exciting, not delightful/delightful, not thrilling/thrilling, not enjoyable/enjoyable, and tedious/stimulating planning their holiday itinerary was using Ryan's Travel's AI. This scale was phrased to ensure no bias was given to participants, to ensure an accurate representation of how hedonic or utilitarian participants' experience with Ryan's Travel's AI was. This was necessary to understand how both manipulations were received by each condition group.

Table 3.4: *Likert Items of Purchase Type*

Likert Items for Purchase Type (LPT)	
Coding:	Likert items (strongly disagree/strongly agree)
Q3_LPTa	This trip is all about pleasurable experiences
Q3_LPTb	This trip will be all about achieving work related goals

Table 3.5: *Purchase Type Manipulation Scale*

Semantic-Differential Items for Purchase Type (PT)	
Coding:	Semantic-differential items
Q4_PTa	Not fun/fun
Q4_PTb	Dull/exciting
Q4_PTc	Not delightful/delightful
Q4_PTd	Not thrilling/thrilling
Q4_PTe	Not enjoyable/enjoyable
Q4_PTf	Tedious/stimulating

3.6.1.2 Artificial intelligence anthropomorphised questionnaire items

The last manipulation check used in this research was created to measure the manipulation of anthropomorphised level that participants were subjected to within the experiment. Two levels were created: low anthropomorphised AI and high anthropomorphised AI; the differences for each condition were in the physical view of the AI - all other aspects of the AI were identical. As shown in Figures 3.1, 3.2 and 3.3, half of the conditions used an audio bar to represent the AI, and the other half used a life-like avatar with human-like facial expressions and movements. Five items were asked using a seven-point semantic differential scale to understand how anthropomorphised participants considered the AI they were subjected to was. This scale was adapted from the work of Kiesler et al. (2008); their study resulted in a Cronbach's alpha coefficient of 0.83. The scale asked five items around how human-like the technology was, based on high or low levels. This scale is presented in Table 3.6.

Table 3.6: *Likert Items for Anthropomorphism Level Scale*

Anthropomorphised Level (ANTL)	
Coding:	Semantic-differential items
Q5_ANTLa	Machine-like/human-like
Q5_ANTLb	Artificial/natural
Q5_ANTLc	Not life-like/life-like
Q5_ANTLd	Robotic/human
Q5_ANTLe	Unsophisticated/sophisticated

3.6.2 Measure for Control Variable

3.6.2.1 Brief mood introspection scale (BMIS) questionnaire items

Before participants were subjected to an environmental stimulus, their current overall mood was measured to understand the effect of mood on consumers' AI adoption intention. To test participants' current overall moods, Mayer and Gaschke's (1988) Brief Mood Introspection Scale (BMIS) was used. This scale is made up of sixteen items, with eight positive emotions and eight negative emotions. Each item is rated on a four-point Likert scale, ranging from definitely "don't feel (XX)" to "definitely feel (VV);" each rating was then changed to a numeric value, depending on whether the emotion was positive or negative. Items were rated as shown in Table 3.7.

Table 3.7: *Brief Mood Introspective Scale (BMIS) Item Values*

	Definitely don't feel	**Do not feel**	**Slightly feel**	**Definitely feel**
Positive Emotions	1	2	3	4
Negative Emotions	4	3	2	1

Participants' positive and negative mood responses were transferred to the values shown in Table 3.7, then all positive and emotional values were added together to create two value totals. Finally, to rate each participant's current overall mood, their overall negative emotion value was subtracted from their overall positive emotion value. This created a score that could be represented as an overall mood, ranging from values of very unpleasant (-10) to very pleasant (10). The items used for this scale are presented in Table 3.8.

Table 3.8: *Brief Mood Introspective Scale (BMIS*)

Brief Mood Introspection Scale (BMIS)	
Coding:	Likert Items (definitely do not feel XX/definitely feel VV)
Q1_BMISa	I am feeling lively
Q1_BMISb	I am feeling happy
Q1_BMISc	I am feeling sad (-)
Q1_BMISd	I am feeling tired (-)
Q1_BMISe	I am feeling caring
Q1_BMISf	I am feeling contented
Q1_BMISg	I am feeling gloomy (-)
Q1_BMISh	I am feeling jittery (-)
Q1_BMISi	I am feeling drowsy (-)
Q1_BMISj	I am feeling grouchy (-)
Q1_BMISk	I am feeling peppy
Q1_BMISl	I am feeling nervous (-)
Q1_BMISm	I am feeling calm
Q1_BMISn	I am feeling loving
Q1_BMISo	I am feeling fed Up (-)
Q1_BMISp	I am feeling active

3.6.3 Measures for Participants' Cognitive Response

3.6.3.1 Credibility of website questionnaire items

Participants were first subjected to one of two scenarios; these were used to put each participant in the correct mind-set to properly digest the short AI video without missing key information in the video. To understand how credible the website and experience was, a three item seven-point Likert scale was used, as shown in Table 3.9. This scale was adapted from the work of Cotte et al. (2005) and Soscia et al. (2019); the scale had a Cronbach's alpha coefficient of 0.87. The three items were tested, rating how realistic, credible, and believable the scenario was.

Table 3.9: *Credibility of Website Likert Scale*

Credibility of website (CoW)	
Coding:	Likert Items (strongly disagree/strongly agree)
Q6_CoWa	This scenario was realistic
Q6_CoWb	This scenario was credible
Q6_CoWc	This scenario was believable

3.6.3.2 Believability of website questionnaire items

Participants were then asked a series of questions to understand how believable the website and experience was. After participants were shown one of two scenarios, they were exposed to one of eight conditions (AI video). To understand how believable the website was, a six item, seven-point Likert scale was used, as shown in Table 3.10. This scale was adapted from the work of Chang (2011); this scale was shown to have a Cronbach's alpha coefficient of 0.94. The six items asked, all had to do with the credibility of each stimulus, by asking how believable, trustworthy, credible, reasonable, convincing, and unbiased the stimulus was to the participant.

Table 3.10: *Believability of Website Scale*

Believability of website (BoW)	
Coding:	Likert Items (strongly disagree/strongly agree)
Q7_BoWa	The experience was believable
Q7_BoWb	The experience was trustworthy
Q7_BoWc	The experience was credible
Q7_BoWd	The experience was reasonable
Q7_BoWe	The experience was convincing
Q7_BoWf	The experience was unbiased

3.6.3.3 Sense of presence with website questionnaire items

This scale has been previously used to understand participants' sense of presence within a virtual environment (Barfield & Hendrix, 1995), as utilised in this study, to understand how present participants were while watching their stimuli. To understand and test participants' sense of presence, a three item, seven-point Likert scale was used, as presented in Table 3.11. This scale was adapted from the work of Barfield and Hendrix (1995); their study resulted in a Cronbach’s alpha coefficient 0.85. Of the six items Barfield and Hendrix (1995) used, three were adapted and used to fit the context of this study. These three items were: “your sense of presence was strong,” “your sense of being there was strong,” and “your sense of inclusion was strong” while watching Ryan’s Travel’s AI video.

Table 3.11: *Sense of Presence with Website Scale*

Sense of Presence with Website (SOP)	
Coding:	Likert Items (strongly disagree/strongly agree)
Q9_SOPa	Your sense of presence was strong while watching Ryan’s Travel’s AI video
Q9_SOPb	Your sense of “being there” was strong while watching Ryan’s Travel’s AI video
Q9_SOPc	Your sense of inclusion was strong while watching Ryan’s Travel’s AI video

3.6.3.4 Involvement of AI and website questionnaire items

This next scale had been previously used to understand and test participants’ involvement with a task (Wilcox et al., 2011). The scale was used in this study, to understand how and to what extent participants felt involved while being exposed to their stimuli. To understand participants’ involvement, a three item, seven-point Likert scale was used, as shown in Table 3.12. The scale was adapted from the work of Wilcox et al. (2011); it was found to have a Cronbach’s alpha coefficient of 0.92. The three items asked were related to how not involved/involved, not interest/interested, and not engaged/engaged participants felt while exposed to their stimuli.

Table 3.12: *Involvement with Website Scale*

Involvement with Website (INV)	
Coding:	Semantic-Differential Scale Items
Q8_INVa	Not involved at all/very involved
Q8_INVb	Not interested at all/very interested
Q8_INVc	Not engaged at all/very engaged

3.6.3.5 Helpfulness of AI questionnaire items

To understand and test the helpfulness of an online environment, this study adapted and used Wu’s (2013) scale for measuring technology helpfulness. To understand and test the helpfulness of an online environment, a three item, seven-point Likert scale was used, as presented in Table 3.13. The scale was shown to have a Cronbach's alpha coefficient of 0.92 (Wu, 2013). The three items used to test technology helpfulness were: "the AI was informative," "the AI was useful," and "the AI was helpful."

Table 3.13: *Helpfulness of AI Technology Scale*

Helpfulness of AI (HAI)	
Coding:	Likert Items (strongly disagree/strongly agree)
Q10_HAIa	The AI was informative
Q10_HAIb	The AI was useful
Q10_HAIc	The AI was helpful

3.6.4 Measures for Participants' Behavioural Response

3.6.4.1 Usage of AI intentions questionnaire items

Participants' usage intention of AI was then asked, using a scale focused on the use and reuse of a similar type of software in the future and previously used to understand participants' acceptance of online robots (Heerink et al., 2010; Tay et al., 2014). Artificial intelligence usage intention was measured using three items on a seven-point Likert scale. The scale was adapted from the work of Tay et al. (2014); the use of this scale in their study resulted in a Cronbach's alpha coefficient of 0.71. The three items asked were: if given the chance, "I think I will use this software," "I am certain to use this software," and "I plan to use this software in the near future." This scale is presented in Table 3.14.

Table 3.14: *Usage Intention of AI Scale*

Usage Intention (UI)	
Coding:	Likert Items (strongly disagree/strongly agree)
Q11_UIa	If given a chance, I think I'll use this software in the near future
Q11_UIb	If given a chance, I'm certain to use this software in the near future
Q11_UIc	If given a chance, I plan to use the software in the near future

3.6.4.2 Purchase intention via AI

To understand participants' willingness to purchase from an online store via AI, this study adapted the following scale (see Table 3.15) used in previous studies (see Jarvenpaa et al., 2000; van der Heijden et al., 2003). The scale uses four items on a seven-point Likert scale to understand participants' wiliness to purchase. This scale was used by Jarvenpaa et al. (2000) and van der Heijden et al. (2003) and resulted in a Cronbach's alpha coefficient of 0.91. The four items asked revolved around a time frame of return to the website and potential purchase, to understand how likely it was that participants would purchase from Ryan's Travel, either in the short term (three months) or longer term (within a year).

Table 3.15: *Purchase Intention via AI Scale*

Purchase Intention (PI)	
Coding:	Likert Items (extremely unlikely/extremely likely)
Q12_PIa	How likely is it that you would return to Ryan's Travel's website?
Q12_PIb	How likely is it that you would consider using Ryan's Travel's services in the short term (within the next 3 months)?
Q12_PIc	How likely is it that you would consider using Ryan's Travel's services in the longer term? (within the next year)?
Q12_PId	For the purchase used in this example, how likely is it that you would use Ryan's Travel's services?

3.6.4 Attention Checks

Attention checks are vital when conducting research via Mechanical Turk. Attention checks are known to be valuable within experimental research, due to their ability to mitigate budgetary requirements and improve the quality of data (Abbey & Meloy, 2017). Numerous attention checks were necessary due to the use of MTurk, as without these, there would be no way to ensure participants had correctly interpreted each question, and instead randomly chose answers in order to receive their remuneration. These attention checks are presented in Appendices H.c and H.e. The first attention check correlated with the stimulus that each participant was exposed to, to ensure participants did not skip the environmental stimuli (video). Two stimulus-specific instructions/questions were used: "please enter the AI's name," and "what was the purpose of the AI?" Answers were dependent on what stimuli participants had been exposed to. The next attention check was in Question Seven. At the end of the website believability question, participants were asked to simply enter "strongly agree." All data was removed from participants who answered the attention check questions incorrectly, to clean the data of any impurities, and remove data from participants who just did the survey for the remuneration without paying attention to the context of the experiment.

3.6.5 Demographic Measures

Lastly, general demographic questions were asked at the end of the survey. This information was collected to produce insights into the sample while also increasing the amount of information gained from the analysis. The demographic questions included those on gender, age, ethnicity, education, and occupation. The questions are presented in Table 3.16.

Table 3.16: *Demographic Questionnaire Items*

Gender	
Coding	Multiple Choice (Single Answer)
Q13-(1)	Male
Q13-(2)	Female
Q13-(3)	Prefer not to say
Q13-(4)	Other (please specify)
Age Bracket	
Coding	Multiple Choice (Single Answer)
Q14-(1)	18-24
Q14-(2)	25-34
Q14-(3)	35-44
Q14-(4)	45-54
Q14-(5)	55-64
Q14-(6)	65-74
Q14-(7)	75-84
Q14-(8)	85 or older
Ethnicity	
Coding	Multiple Choice (Multiple Answer)
Q15-(1)	Caucasian
Q15-(2)	African American
Q15-(3)	American Indian
Q15-(4)	Asian American
Q15-(5)	Hispanic American
Q15-(6)	Native Hawaiian
Q15-(7)	Other (please specify)
Education	

Coding	Multiple Choice (Single Answer)
Q16-(1)	Some high school
Q16-(2)	High school diploma
Q16-(3)	Bachelor’s degree
Q16-(4)	Master’s degree
Q16-(5)	PhD or doctoral degree
Q16-(6)	Other (please specify)
Occupation	
Coding	Multiple Choice (Single Answer)
Q17-(1)	Employed full time
Q17-(2)	Employed part time
Q17-(3)	Unemployed looking for work
Q17-(4)	Unemployed not looking for work
Q17-(5)	Retired
Q17-(6)	Student
Q17-(7)	Disabled
Q17-(8)	Prefer not to say
Q17-(9)	Other (please specify)

3.7 Experiment Procedure

3.7.1 Participant Selection

All participants were recruited using Amazon’s MTurk, an online workforce platform that provides “immediate access to a large and diverse subject pool, and allows researchers to control the experimental context” (Horton et al., 2011, p. 399). Mechanical Turk was utilised because of the efficiency of the software, and the validation that the online platform has been associated with for experimental research (see Mellis & Bickel, 2020; Paolacci et al., 2010). Mechanical Turk offers a wide range of benefits for experimental research, such as allowing participants to complete an experiment without having to interact with an experimenter, which removes any possibility of experimenter bias (Paolaaci et al., 2010), and subjective crosstalk (Edlund et al., 2009). Online experiments using MTurk have been shown to have very high validity. Horton et al. (2011) noted that “online experiments…can be just as valid – both internally and externally – as laboratory and field experiments, while requiring far less money and time to design and conduct” (p. 399).

Residents in the USA were selected for the sample due to the travel restrictions caused by the COVID-19 pandemic at the time of the study (December 2020). To overcome the limitations of an overseas AI itinerary, the experiment limited the technology to creating domestic itineraries within the USA. This allowed all participants to imagine they were actually using the AI for the intended purpose, as demonstrated in the scenario they were presented with. The context of this research required participants to have some knowledge of the process of planning a domestic holiday or business trip itinerary within the USA. To ensure this, MTurks screening feature was used to ensure participants met this criterion before being subjected to the experiment. The screening question was:

> *Have you been on/or planned a business trip/holiday in the last 12 months (this involves either flying or driving to the business trip/holiday destination)?*

Workers were also required to have a high MTurk approval rating, a screening feature that MTurk utilises to ensure high quality workers are used for experimental research. Participants needed an approval rating with previous Human Intelligence Tasks (HITs) of greater than 99%. The online experiment was created using Qualtrics, an online survey environment perfect for the setup, distribution, and collection of data (Barnhoorn et al., 2015). Utilising Qualtrics' randomiser setting, eight separate video blocks were created, and 80 participants randomly assigned to one of eight experimental conditions.

Participants were offered an incentive of USD $1.00 as remuneration for completing the Qualtrics questionnaire; the time commitment for participants was estimated to be 10 to 15 minutes. The experiment was facilitated by MTurk Data, an academic survey consultant who dealt with all the requirements of MTurk to ensure the experiment ran as designed. This included the screening check, ensuring all participants were eligible, and taking care of participants' remuneration. Several further attention checks were used to ensure blind responses were not taking place, and questions on the context of each video were asked as well as a question asking participants to select specific answers for some items. Any checks incorrectly answered resulted in removal of that participant's data.

Data collection occurred from 7th to 8th December 2020; during this period, 644 responses were collected.

3.7.2 Ethical Considerations

This research first sought approval from the University of Canterbury Human Ethics Committee. The research proposal was submitted in September 2020, and approval granted 5th October 2020. The ethics approval letter is presented in Appendix A. All participants were advised to read the information sheet (Appendix H.a) before beginning the experiment. This was to inform participants of the purpose and procedure of the study; participants then had to give consent on the consent form (Appendix H.a) to ensure they understood the information sheet and to make sure participants consented voluntarily. Participants were advised that their results would be anonymous, and that no personal information would be collected.

3.7.3 Online Experiment

The survey was hosted on Qualtrics, an online survey developer than allows for simple creation and distribution of anonymous survey links. This link was given to participants through the Human Intelligence Tasks (HITs) section of MTurk. Mechanical Turk workers were required to have an HIT approval rate above 99% and a minimum of 1000 HITs completed; this was a requirement to ensure a professional standard of data.

The experiment involved showing each participant one of eight videos, which was preceded by an evaluation of their current mood and a wide range of survey questions around the credibility and believability of the website, participants' perceptions of involvement with the website, their sense of presence and technology helpfulness, and their purchase and AI usage intentions with website. Each of the seven blocks of the survey is explained in detail next.

3.7.3.1 Block One – Information and consent

In Block one, participants were shown the information sheet and consent form (Appendix H.a). This included an overview of the research's purpose, which was to understand the direct effects of purchase type, multiple AI genders, and anthropomorphism level, on participants' cognitive and behavioural responses to AI. The information sheet also identified the requirements of each participant, a description of what would happen with the data, and explanation of how long participation would take. Participants were then asked for their consent to participate in the experiment. Next, participants were asked a screening question: "have you been on/or planned a business trip/holiday in the last 12 months (this involves either flying or driving to the business trip/holiday destination)?" Participants who selected "no" to this question were taken to the end of the questionnaire, where their participation in the experiment concluded.

3.7.3.2 Block Two – BMIS (mood testing)

After passing the screening question, participants were asked to rate 16 items (Appendix H.b) based on their mood at the beginning of the experiment, before being exposed to one of eight stimuli. Participants rated eight negative and eight positive items on a four-point Likert scale, ranging from "definitely do not feel" to "definitely feel." The data were then used to create an overall mood score, by adding the positive and negative items together and then subtracting the negative value from the positive value, to calculate an overall mood level ranging from -10 (very unpleasant) to 10 (very pleasant) for each participant.

3.7.3.3 Block Three – Environmental stimuli exposure

Participants were then randomly assigned one of eight experimental stimuli. Each condition had a different manipulation of AI gender (male vs female), purchase type (business trip vs holiday), and anthropomorphism level (low vs high). Accompanying each video was one of two scenarios, to give participants further information about the purpose of the AI. The scenarios are presented next, and one of the eight environmental stimuli is included in Appendix H.c.

3.7.3.3.1 Scenario One: Hedonic Holiday Itinerary Scenario

Imagine you are planning your next holiday; you are wanting to go away somewhere that will allow you to have a fun and relaxing holiday, lined up with exciting tourist activities that will be both enjoyable and stimulating. But you are unsure where in America you should visit next or what activities or experiences you should have while there. Fed up with traditional travel agencies and tour operator services you decide to use Ryan's Online Travel Service for the first time to plan and book your upcoming holiday somewhere within the United States of America. Ryan's Travel offers a booking capability that utilises artificial intelligence to plan a personalised itinerary for people looking to go on holiday. The software will ask a variety of holiday questions to determine your holiday needs, wants and expectations, to create a fun, exciting, stimulating, and personalised itinerary. Your information will then be analysed and used in conjunction with millions of previous travel itineraries and information found online to match your personal preferences with a *destination, accommodation, and activities. After you accept your day-by-day personalised itinerary, Ryan's Travel will book all flights, accommodation, and activities for you and your travelling party, saving hours of time and hassle.*

3.7.3.3.2 Scenario Two: Utilitarian Business Trip Itinerary Scenario

Imagine you are planning your next business trip; you are looking to fly to Los Angeles. The purpose of this trip is purely for business purposes and you expect a dull and tedious trip, which isn't an issue as you will be busy throughout most of the day. In saying this you are still unsure what activities or experiences you should have while there. Fed up with traditional work-related travel agencies and tour operator services you decide to use Ryan's Online Travel Service for the first time to plan and book your upcoming business trip. Ryan's Travel offers a booking capability that utilises artificial intelligence to plan a personalised itinerary for people looking to plan their business trip. The software will ask a variety of questions to determine your business trip needs, wants, and expectations, to create a structured, organised, and well-planned itinerary. Your information will then be analysed and used in conjunction with millions of previous travel itineraries and information found online to match your personal preferences with accommodation and activities. After you accept your day-by-day personalised itinerary, Ryan's Travel will book all flights, accommodation and activities for you and your travelling party, saving hours of time and hassle.

Participants were forced to stay on this block for 140 seconds, giving them enough time to read the scenario and watch the 105 seconds video. Participants then had to answer two attention check questions (Appendix H.c). All questions needed to be answered correctly for participants' data to be included in the final sample. Participants were allowed to progress after 140 seconds, provided both attention checks were answered correctly. If answered incorrectly, participants' involvement with the experiment was concluded.

3.7.3.4 Block Four – Manipulation checks

Following participants' exposure to their stimuli, manipulation check questions (Appendix H.d) were asked for all independent and control variables. The order for all questions remained the same for each participant to ensure no bias was caused by the question order. First, participants were asked to respond to four items about their experience with the AI voice, to ensure they recognised the AI as either male or female.

Next, two items were asked to ensure participants understood the purpose of the itinerary. To ensure that the manipulation of the two types of products (hedonic/utilitarian) were recognised, a six-item semantic-difference scale was used. At one end, the items were strongly hedonic, and at the other, strongly utilitarian, to provide an insight into how the manipulations were viewed by participants.

Lastly, participants were asked questions on a five-point semantic-difference scale to understand their views on the manipulation of anthropomorphism for both levels of AI. At one end of the scale the items were strongly machine oriented, and at the other end, items were strongly human oriented.

3.7.3.5 Block Five – Cognitive responses

In Block Five (Appendix H.e), participants were asked multiple questions around the credibility of the stimuli. One question comprised three items about the credibility of the AI website. Next, one question comprised six items about the believability of the AI website, and an additional seventh item was included as an attention check to ensure blind responding was not occurring. This item was "please enter strongly agree." Any participant who answered incorrectly had their data removed. After this, a three item question was asked about participants' involvement during their experience with Ryan's Travel's AI website. Lastly, they were asked about their sense of presence while watching the AI video; four items were asked. All questions in this section were rated using a seven-point Likert scale ranging from "strongly agree" to strongly disagree."

3.7.3.6 Block Six – Cognitive and behavioural responses

In Block Six (Appendix H.f), participants were asked questions around their attitude towards the AI that they were exposed to. First, a question about how helpful the AI would be was asked, using three items on a seven-point Likert scale ranging from "strongly agree" to "strongly disagree." Next, a question about the anthropomorphised validity was asked to understand participants' views on the AI's personality. Following this, two scales were used to understand participants' likelihood of reusing this or similar AI software, and how likely it was that they would use this software again in the near to distant future.

3.7.3.7 Block Seven – Demographics

In this final block (Appendix H.g) of the survey, participants were asked demographic questions about their age, gender, occupation, ethnicity, and education. Participants were then provided a survey code to enter into MTurk, as one final attention check. Participants' MTurk worker ID was also recorded to ensure a worker did not undertake the experiment another time, either in the primary research or the pre-test.

3.8 Pre-Test

Before the final data collection was conducted, the entire experiment and questionnaire was tested with a full pre-test. This was necessary to ensure all independent variable manipulations were perceived by participants as intended. Furthermore, the pre-test was used to test the reliability and validity of the scales used in the questionnaire. The pre-test ensured the data collection operated as planned, and checked for issues such as time taken by participants, data collection and interpretation, and ensuring they watched and read all the stimuli before beginning the questionnaire.

3.8.1 Pre-Testing Sample and Results

In total, 80 participants completed the pre-test. These participants were found through MTurk, and received USD $1 remuneration. All 80 participants completed the experiment, which was predicted to occur, due to the requirement for participants to have a 99% or above HIT approval rate and a minimum of 1000 completed HITs. The pre-test found that on average, the experiment took nine minutes and three seconds to complete; all functions within the questionnaire were found to work as intended.

The structure and reliability of the measurement were checked with a Principal Component Analysis and Cronbach alpha reliability analysis on all scales to ensure reliability. A Principal Component Analysis was used to test each construct; all scale items with a loading score of >0.30 were suppressed, and any items considered to load on to multiple factors were deemed to be cross-loading, and therefore removed. Items with low communality scores of >0.50 were also removed.

3.9 Chapter Summary

This chapter outlined the processes followed in this quantitative research, to test the hypotheses discussed in Chapter Three. The experiment created was a 2 x 2 x 2, between-subjects factorial design to test the effects of purchase type (hedonic vs utilitarian), AI gender (male vs female), and anthropomorphism level (high vs low). This chapter explained the process for developing the eight unique stimuli, justified the use of videos to present each stimulus to participants, and the explanation for determining the levels of manipulation for each of the three independent variables. A pre-test was used to ensure the manipulation of all three independent variables was accurately reflected by participants. This explanation was followed by an explanation of the experimental procedure, participant selection, ethical considerations, experiment procedures and the seven blocks used in the survey on Qualtrics. The next chapter discusses the results found from the between-subjects factorial design.

Chapter 4. Findings

4.1 Introduction

This chapter discusses the process of statistical analysis conducted after the collection of the experimental design data. The chapter begins with an explanation of the studies overall composition, sample size, descriptive statistics, and the recoding that was required. Following this, a section on Principle Component Analysis and reliability testing is provided for each independent, dependent, and covariate variable. This is then followed by a section on the manipulation checks for each independent variable relating to purchase type, AI gender, and anthropomorphism levels. Next, the analyses and results for each hypothesis are presented. First the 12 hypotheses are analysed using a variety of analyses including: a three-way ANCOVA, independent t-tests, and linear regression, this is then followed by a summary of the hypothesis results. Following this, a structural equation model (SEM) is presented to further conclude and strengthen the findings of this study. Lastly, a summary of all supported and unsupported hypotheses is presented.

4.2 Sample Composition and Statistics

4.2.1 Sample Composition

The sample composition was analysed using five separate descriptive statistics, as presented in Table 4.1. The gender divisions within the sample were relatively even between female and males, with 51% of participants responding as female, 48.7% being male, and 0.3% preferring not to specify their gender. The ages of participants were spread across four groups: 30.6% of the sample were aged 35 to 44, 28.3% were aged 25 to 34, 19.6% were aged 45 to 54, and 13.7% were aged 55 to 64. 5.1% were aged 65-74, 2% were aged 18-24, and 0.8% were aged 75-84.

The ethnicity splits were heavily skewed due to the characteristics of Amazon's MTurk workers: 85.5% of the sample identified as Caucasian, 5.7% identified as African American, 4.2% identified as Asian American, 2.3% identified as Hispanic American, and 2% of the sample identified as other, all indicating they were of mixed races.

The sample comprised a mix of education levels: 52.9% of the sample's highest education was that of a bachelor's degree, 19.9% had a master's degree, 18.3% had a high school diploma, and 4.2% had a PhD or other doctoral degree. The remaining 4.4% selected "other" as their highest form of education, which was followed by numerous explanations, most of which related to an "Associate" degree, which is the same as a bachelor's degree and some further college (i.e., university) education. These responses were most likely due to participants not reading the question correctly, explanations such as "some college" were frequent and meant that participants' highest form of education was a high school diploma. There was also some misunderstanding about what a bachelor's degree was in a USA context.

The final demographic question asked participants about their current occupation. Results indicated that 76.8% of the sample were employed full-time, 9.5% were employed part-time, 4.7% were retired, 3.3% were unemployed but not looking for work, 2.3% selected other, 1.0% were unemployed looking for work, 1.0% were disabled, 0.8% preferred not to say, and 0.7% were students.

Table 4.1: *Research Sample Demographics*

Demographic Variable	Category	Count	Percent
Gender	Female	312	51%
	Male	298	48.7%
	Prefer not to say	2	0.3%
Age	18-24	12	2%
	25-34	173	28.3%
	35-44	187	30.6%
	45-54	120	19.6%
	55-64	84	13.7%
	65-74	31	5.1%
	75-84	5	0.8%
Ethnicity	Caucasian	523	85.5%
	African American	35	5.7%
	American Indian	2	0.3%
	Asian American	26	4.2%
	Hispanic American	14	2.3%
	Other (please specific)	12	2.0%
Education	Some high school	1	0.2%
	High school diploma	112	18.3%
	Bachelor's degree	324	52.9%
	Master's degree	122	19.9%
	PhD or other doctoral degree	26	4.2%
	Other (please specify)	27	4.4%
Occupation	Employed full time	470	76.8%
	Employed part time	58	9.5%
	Unemployed looking for work	6	1.0%
	Unemployed not looking for work	20	3.3%
	Retired	29	4.7%
	Student	4	0.7%
	Disabled	6	1.0%
	Prefer not to say	5	0.8%
	Other (please specify)	14	2.3%

4.2.2 Sample Size

This study's final data collection was collected in one stage, from the 7th to 8th of December 2020; this used one participant pool through Amazon's MTurk. MTurkData, a third-party website, was contracted to ensure all participants were experienced on the website (MTurk), were not a part of the pre-test, answered all questions correctly, and had valid MTurk IDs. The use of MTurkData was needed to ensure no issues occurred on the MTurk platform. This data collection resulted in a total sample size of 644 participants.

All participants were required to read the information sheet provided and consent to being part of the experiment (Appendix H.a). A screening question was asked to ensure participants had been on a holiday or business trip within the past 12 months; zero participants selected “no” for this question. Next, three attention checks were included in Blocks Three and Five (see Section 3.7.3). The first two attention check questions asked participants the name of the AI and its purpose. This check removed 20 participants: three selected the incorrect name of the AI, and 17 selected the incorrect purpose of the AI. The final attention check asked participants to select “strongly agree”: 12 participants selected incorrectly, therefore, their data was removed from the experiment. Overall, data from 32 participants were removed from the study, resulting in a final sample size of 612 participants.

4.2.3 Descriptive Statistics

Descriptive statistics of each scale are presented in Table 4.2. The table presents each scale’s mean, standard deviation, skewness, and kurtosis. Skewness and kurtosis were analysed to show the distribution for each scale. The results showed that the independent variables of “purchase type” and “anthropomorphism level” had a relatively normal distribution (as shown by their kurtosis scores of 0.04), whereas AI gender had a non-normal distribution with a very sharp peak with a kurtosis score of 5.86. This was expected however, as the items used to test this manipulation were proposed to produce a definitive answer of what gender participants perceived the AI to be. All independent variables were skewed to the left, with skewness scores of between -.84 and -.66, and all dependent variables skewed to the left, with skewness scores of between -1.45 and -.71. “Website credibility,” “website believability,” “website involvement,” and “technology helpfulness” had a standard normal distribution in their means and kurtosis scores of between 2.83 and 1.12. “Website sense of presence,” “usage,” and “purchase intentions” had negative kurtosis scores of between -0.23 and -0.89, with a flat and broad distribution. The covariate of users’ overall moods (BMIS) skewed slightly to the left (skewness = -0.13) with a relatively normal distribution (kurtosis = 1.67).

Table 4.2: *Descriptive Statistics for Total Scale Variables*

Scale	Mean	Std Dev.	Skewness	Kurtosis
Independent Measures:				
AI gender	3.86	0.32	-0.84	5.86
Purchase type	4.99	1.53	-0.73	0.04
Anthropomorphism level	4.73	1.29	-0.66	0.04
Cognitive Response Measures:				
Website credibility	5.70	1.07	-1.45	2.83
Website believability	5.45	1.03	-1.07	1.80
Website sense of presence	4.92	1.51	-0.71	-0.23
Website involvement	5.42	1.30	-1.16	1.12
Technology helpfulness	5.53	1.22	-1.22	1.56
Behavioural Response Measures:				
Usage intention	4.25	1.74	-0.41	-0.82
Purchase intention	4.43	1.80	-0.52	-0.89
Control Variable Measures:				
BMIS	2.36	0.30	-0.13	1.67

4.3 Recoding

To understand a participant's mood at the time of the experiment, the Brief Mood Introspective Scale (BMIS) had to be recoded. All negatively worded questions were recoded inversely (1 = 4, 2 = 3, 3 = 2, 4 = 1). A user's overall mood variable was created by totalling the negative and positive BMIS values separately, and subtracting the negative total from the positive total to create a user's overall mood value for the time of the experiment. Next, "AI gender," "purchase type," and "anthropomorphism level" independent variables were created, each with two values: ("AI gender": 1 = "male," 2 = "female"), ("purchase type": 1 = "hedonic," 2 = "utilitarian") and ("anthropomorphism level": (1 = "low," 2 = "high"). After all variables had been recoded, the scales were tested for dimensionality and reliability; all independent variable scales were then checked for their manipulation levels. Question Two was recoded to allow for accurate analysis of the manipulation checks. Items b and d of Question Two needed to be recoded so an independent t-test could be run. These items had to be reversed to allow for accurate reporting of the mean difference; the changes were as follows: 1 = 7, 2 = 6, 3 = 5, 5 = 3, 6 = 2 and 7 = 1.

4.4 Principal Component Analysis, Reliability Testing, and Scale Structure

Consistent with the pre-test analysis, the structure and reliability of the measurement scales were tested using a Principal Component Analysis and Cronbach's alpha reliability analysis. All survey questions were analysed using Principal Component Analysis with Varimax rotation to assess the dimensionality of all scales used within the questionnaire. To reduce error within the data, all scale items with a communality score of less than 0.50 were deleted, and coefficients less than 0.30 were withheld. Cross-loading was deemed to have occurred if an item equally loaded on to two or more factors; if this occurred the item was removed. All data explained in this section can be found in Table 4.3.

Table 4.3: *Summary of Principle Component Analysis and Reliability Analysis*

Scale	Variance Explained	Communality Scores	Cronbach's Alpha	Number of Items
AI gender	96.71%	0.96 - 0.97	.99	4
Purchase type	87.02%	0.82 - 0.91	.97	6
Anthropomorphism level	89.93%	0.89 - 0.91	.96	4
Credibility of website	91.34%	0.89 - 0.93	.95	3
Believability of website	82.52%	0.77 - 0.89	.95	5
Sense of presence	90.70%	0.89 - 0.92	.95	3
Involvement	85.97%	0.82 - 0.91	.92	3
Helpfulness of AI	88.90%	0.83 - 0.93	.94	3
Usage intention of AI	95.50%	0.94 - 0.96	.98	3
Purchase intention via AI	88.30%	0.78 - 0.92	.95	4
BMIS	66.15%	0.55 - 0.75	.92	16

4.4.1 Environmental Stimuli Scale Measures

4.4.1.1 Artificial intelligence gender manipulation

The four items adapted from McAleer et al.'s (2014) work were used to assess participants' perceptions of the gendered AI voices in the experiment, and resulted in high communality scores of between 0.96 and 0.97; loaded on to a single factor, and explained 96.71% of the variance.

The adapted scale has been used previously to understand participants' views on gender in experimental design studies and was shown to have ranging reliability, with Cronbach's alpha coefficients reported of between 0.88 to 0.98 (McAleer et al., 2014). The Cronbach's alpha coefficient resulting from this scale in this study was 0.99.

4.4.1.2 Purchase type manipulation

The six items adapted from Hepola et al.'s (2020) work, was used to understand the manipulation of AI purchase type that participants perceived. This scale was found to have high communality scores of between 0.82 and 0.91. The six items loaded on to a single factor and explained 87.02% of the variance.

Previous authors have used this scale to understand participants' perceptions of hedonic and utilitarian purchase types in experimental design studies, and results were found to have ranging reliability, with Cronbach's alpha coefficients reported of 0.93 to 0.96 (Hepola et al., 2020). The Cronbach's alpha coefficient resulting from the scale in this study was 0.97.

Question Three was created to further determine the manipulation of purchase type stimuli; however, Question Four was perceived perfectly by participants. Because of this, Question Three was removed from the analysis as it served no purpose for the analysis of purchase type manipulation, contrary to its original purpose.

4.4.1.3 Anthropomorphism level manipulation

Analysis of the five items adapted from McAleer et al.'s (2014) work resulted in the removal of one item (Q5_HAIe) due to a communality score of 0.4 or less (Costello & Osborne, 2005). The analysis was re-run with four items, which then showed strong communality scores of 0.89 to 0.91. All four items loaded on to a single factor; this factor explained 89.93% of the variance.

Previous authors have used this scale to understand participants' views on the anthropomorphism level and life-likeness of a robotic avatar in experimental design studies, and found it had ranging reliability, with Cronbach's alpha coefficients reported of 0.83 (McAleer et al., 2014). The Cronbach's alpha coefficient resulting from this scale in this study was 0.96.

4.4.2 Cognitive Response Measures

4.4.2.1 Website credibility

The three items adapted from Soscia et al.'s (2019) work were used to understand the credibility of an AI website experience, and found to have high communality scores of 0.89

to 0.93. All three items loaded on to a single factor; this factor explained 91.34% of the variance.

Previous authors have used this scale to understand participants' views on the credibility of an advertisement in experimental design studies, and found it had high reliability, with Cronbach's alpha coefficients reported of 0.87 (Cotte et al., 2005; Soscia et al., 2019). The Cronbach's alpha coefficient resulting from this scale in this study was 0.95.

4.4.2.2 Website believability

Analysis of the six items adapted from Chang's (2011) work resulted in the removal of one item (Q7_BAIEf) due to a communality score of 0.4 or less (Costello & Osborne, 2005). This adjustment resulted in five items being used; communality scores for these ranged between 0.77 and 0.89. The five items loaded on to a single factor and explained 82.52% of the variance.

Previously this scale has been used to understand participants' attitudes about the believability of an advertisement in experimental design studies, and was shown to have strong reliability, with Cronbach's alpha coefficients reported of 0.94 (Chang, 2011). The Cronbach's alpha coefficient resulting from this scale in this study was 0.95.

4.4.2.3 Website sense of presence

The three items adapted from Barfield and Hendrix's (1995) work were used to understand participants' sense of presence while using the AI website in the experiment, and found to have high communality scores of between 0.89 and 0.92. All three items loaded on to a single factor; this factor explained 90.70% of the variance.

Previous authors' use of this scale has been to understand participants' sense of presence during a task in experimental design studies. This was shown to have high reliability, with Cronbach's alpha coefficients reported of 0.85 (Barfield & Hendrix, 1995). The use of this scale resulted in a Cronbach's alpha coefficient of 0.95 in this study.

4.4.2.4 Website involvement

The three items adapted from Wilcox's (2011) work were used to understand how involved participants felt in their decision-making process while participating in the experiment. These items showed high communality scores of between 0.82 and 0.91. All three items loaded on to a single factor; this factor explained 85.97% of the variance.

Previous authors have used this scale to understand participants' involvement in a task in experimental design studies, and found it had high reliability, with Cronbach's alpha coefficients reported of 0.85 (Wilcox et al., 2011). The Cronbach's alpha coefficient resulting from this scale used in this study was 0.92.

4.4.2.5 Technology helpfulness

The three items adapted from Wu's (2013) work were used to understand how helpful participants perceived the AI website. These items showed high communality scores of between 0.83 and 0.93. All three items loaded on to a single factor; this factor explained 88.90% of the variance.

Previous authors have used this scale to understand participants' opinions on the helpfulness of a technology in experimental design studies. It was shown to have high reliability, with Cronbach's alpha coefficients reported of 0.92 (Wu, 2013). The Cronbach's alpha coefficient resulting from this scale in this study was 0.94.

4.4.3 Behavioural Response Scale Measures

4.4.3.1 Usage intention

The three items adapted from Tay et al.'s (2014) work were used to understand the likelihood of continued use of a similar software. These items showed high communality scores of between 0.94 and 0.96. All three items loaded on to a single factor; this factor explained 95.50% of the variance.

Previous authors have used this scale to understand participants' acceptance of robots in the future in experimental design studies. It was shown to have high reliability, with Cronbach's alpha coefficients reported of 0.71 (Tay et al., 2014). The Cronbach's alpha coefficient resulting from this scale used in this study was 0.98.

4.4.3.2 Purchase intention

The four items adapted from Jarvenpaa et al.'s (2000) work were used to understand participants' purchase intention via AI, of tourism. These items showed high communality scores of between 0.78 and 0.92. All four items loaded on to one single factor; this factor explained 88.30% of the variance.

Previous authors have used this scale to understand participants' purchase intention of technology in experimental design studies. It was shown to have strong reliability, with Cronbach's alpha coefficients reported of 0.91 (Jarvenpaa et al., 2000; Van der Heijden et al., 2003). The Cronbach's alpha coefficient resulting from this scale in this study was 0.95.

4.4.4 Control Variable Scale Measures

4.4.4.1 Brief mood introspective scale

The sixteen items representing participants' Brief Mood Introspective Scale created by Mayer and Gaschke (1988) had communality scores between 0.55 and 0.75. This scale resulted in a Cronbach's alpha coefficient of .92. Previous uses of this scale did not report a Cronbach's alpha coefficient. The result found in this analysis was therefore considered a very positive sign.

4.4.5 Removed Items

All items removed from the data analysis are presented in Table 4.4.

Table 4.4: *Removed Scale Items*

Scale Item	Communality score	Cronbach alpha with item	Cronbach alpha with item deleted
Q5_HAIe	.400	.92	.96
Q7_BAIEf	.366	.92	.95

4.5 Independent Variable Manipulation Checks

As discussed in Section 3.6, all three independent variables were tested using manipulation checks, to measure participants' perceptions of purchase type, AI gender, and anthropomorphism level. In the following section, tables presenting each manipulation's mean scores, and independent sample t-tests results, provided an understanding of participants' perceptions of the study's independent variable manipulations.

4.5.1 Gender Manipulation Check

The reliability score for the artificial intelligence gender manipulation was shown to slightly increase by 0.01 between the pre-test and the main study. Furthermore, mean scores were only found to decrease slightly between the pre-test and the main study for all items, with very minimal reductions identified (Table 4.5).

Table 4.5: *AI Gender Mean Scores*

Scale Item		Pre-Test		Main Study	
		Mean	**Std Dev.**	**Mean**	**Std Dev.**
Q2_HVa	I considered the AI to be masculine	3.96	2.44	3.94	2.35
Q2_HVb	I considered the AI to be feminine	3.94	2.38	3.75	2.39
Q2_HVc	The voice I experienced on the website sounded like a male voice	4.00	2.55	3.97	2.52
Q2_HVd	The voice I experienced on the website sounded like a female voice	3.85	2.52	3.77	2.53
Total Scale		3.94	0.40	3.86	0.32
Cronbach's Alpha		.98		.99	

To determine how effective the AI gender experimental manipulations were, an independent samples t-test was conducted (Table 4.6). This analysis was used to understand the significant ($p < .05$) difference between each gender that participants were subjected to. Artificial intelligence gender was found to differ between the two conditions, as evidenced in the independent samples t-test, ($t = 78.23$, $p = .000$) between male and female AI conditions (found in Table 4.6). The mean difference between male AI gender ($\bar{x} = 6.38$) and female AI gender ($\bar{x} = 1.79$) conditions was 4.59. Furthermore, the analysis found the scale to be statistically significant ($p = .000$). Manipulation of both AI genders were successfully perceived as intended.

Table 4.6: *AI Gender Independent T-Test Manipulation Check*

Sample Statistics					
AI Gender	**Mean**	**Std Dev.**	**t-test**	**Mean Difference**	**Sig.**
Male	6.38	0.63	78.23	4.59	.000
Female	1.79	0.81			

4.5.2 *Purchase Type Manipulation Check*

The reliability score for the purchase type manipulation was shown to increase by 0.06 between the pre-test and the main study. However, mean scores were shown to decrease between the pre-test and the main study for all items, with reductions found between 0.53 and 0.67 (Table 4.7).

Table 4.7: *Purchase Type Mean Scores*

Scale Item		Pre-Test Mean	Pre-Test Std Dev.	Main Study Mean	Main Study Std Dev.
Q4_SPTa	Not fun/fun	5.70	1.10	5.15	1.59
Q4_SPTb	Dull/exciting	5.55	1.39	5.02	1.63
Q4_SPTc	Not delightful/delightful	5.69	1.21	5.02	1.65
Q4_SPTd	Not thrilling/thrilling	5.04	1.40	4.48	1.69
Q4_SPTe	Not enjoyable/enjoyable	5.94	1.10	5.40	1.58
Q4_SPTf	Tedious/stimulating	5.63	1.42	5.05	1.64
Total Scale		5.59	1.07	5.02	1.51
Cronbach's Alpha		.91		.97	

To determine how effectively purchase type manipulation was interpreted, an independent samples t-test (Table 4.10) was conducted. This analysis was used to understand the significant ($p < .05$) difference between participants' perceived purchase type that they were subjected to. "Purchase type" was found to have a significant difference, as determined through an independent samples t-test, ($t = 12.22$, $p = 0.017$) between hedonic and utilitarian purchase conditions (Table 4.8). The mean difference between hedonic purchase type ($\bar{x} = 5.69$) and utilitarian purchase type ($\bar{x} = 4.34$) conditions was 1.35. Furthermore, the analysis found the scale to be statistically significant ($p = .017$). Manipulation of both purchase types were successfully perceived as intended.

Table 4.8: *Purchase Type Independent T-Test Manipulation Check*

Sample Statistics					
Purchase Type	**Mean**	**Std Dev.**	**T-test**	**Mean Difference**	**Sig.**
Hedonic	5.69	1.28	12.22	1.35	.017
Utilitarian	4.34	1.44			

4.5.3 Anthropomorphism Level Manipulation Check

The AI anthropomorphism level manipulation scale used in the main study was altered after the original scale was shown to be non-significant in the pre-test. Because of this, the prior scale used to test anthropomorphism level was re-created between the pre-test and main study. A semantic-differential five-point scale was used to determine how participants perceived the manipulation of anthropomorphism level (see Table 4.9). As discussed in Section 4.4.1, Question Q5_HAIe was removed due to a low communality score of 0.4 or less (Costello & Osborne, 2005).

Table 4.9: *Anthropomorphism Level Mean Scores*

		Main Study	
Scale Item (Semantic-Differential)		**Mean**	**Std Dev.**
Q5_HAIa	Machine-like/human-like	2.97	1.65
Q5_HAIb	Artificial/natural	2.75	1.60
Q5_HAIc	Not life-like/life-like	3.05	1.71
Q5_HAId	Robotic/human	2.72	1.67
Total Scale		2.88	1.57
Cronbach's Alpha		.96	

To determine how effective the anthropomorphism level manipulation was, an independent samples t-test (Table 4.10) was conducted. This analysis was used to understand the significant ($p < .05$) difference between participants' perceived purchase type that they were subjected to. Anthropomorphism level was found to have no significant difference, as determined through the independent samples t-test, ($t = -1.445$, $p = .149$) between low and high anthropomorphism level conditions (Table 4.10). The mean difference between low anthropomorphism level ($\bar{x}$ = 2.78) and high anthropomorphism level ($\bar{x}$ = 2.96) conditions was 0.184. Furthermore, the analysis found the scale to be statistically non-significant (p = .149). Manipulations of anthropomorphism levels were unsuccessfully perceived as intended.

Table 4.10: *Anthropomorphism Level Independent T-Test Manipulation Check*

Sample Statistics					
Anthropomorphism Level	**Mean**	**Std Dev.**	**T-test**	**Mean Difference**	**Sig.**
Low	2.78	1.52	-1.445	0.184	.149
High	2.96	1.63			

4.5.4 *Manipulation Check Summary*

All independent variables continued to be used to understand both the direct effect on participants' behavioural responses (usage and purchase intention) and the effects on participants' cognitive responses (website credibility, website believability, website sense of presence, website involvement, and technology helpfulness). Although the manipulation of anthropomorphism level was found to be unsuccessfully perceived by participants, a decision was made to continue with the analysis as planned, by including "anthropomorphism level" as an independent variable. If anthropomorphism levels had a significant effect on their own, the analysis would have discussed other explanations for why this occurred. However, this research was interested in understanding the interaction effects of purchase type, AI gender, and anthropomorphism levels, in relation to the hypotheses presented in Chapter 2.

4.6 Hypothesis Testing

After conducting the manipulation checks, two statistical methods were conducted to answer the three hypothesis streams. For H1 and H2, a series of three-way Analysis of Covariance (ANCOVA), a statistical method used to observe variance within data, were conducted to understand the interaction effects of purchase type, AI gender, and anthropomorphism level on all cognitive and behavioural responses. The covariates of users' overall moods were tested to determine their effects on participant responses. The three-way ANCOVA analysis was completed to determine how the three independent variables, and covariate, resulted in a significant ($p < .05$) interaction effect on the studies behavioural and cognitive responses. Partial eta squared values ($\boldsymbol{\eta_p^2}$) were calculated for each hypothesis to determine the effect sizes of each of the independent variables on each dependent variable. To test the H3 hypothesis stream, a series of linear regression analyses were conducted to understand how each of the five cognitive responses could be used to predict participants behavioural response (usage and purchase intention via AI).

4.6.1 *H1a: Purchase Type, and Artificial Intelligence Gender, and Anthropomorphism Level, will have a Direct Effect on Participants' AI Usage Intention*

Hypothesis 1a proposed that the interaction of purchase type, AI gender, and anthropomorphism level, would directly affect participants' AI usage (behavioural response) intention. To test this hypothesis, a three-way ANCOVA analysis was run. The three independent variables and one covariate (users' overall mood) were tested to understand their effects on participants' intention to use the AI. Results of this analysis are presented in Tables 4.11 and 4.12.

Table 4.11: *Participants' Perceived AI Website Usage Intention Across Experimental Stimuli*

Hypothesis Variables			Usage Intention	
AI Gender	**Purchase Type**	**Anthropomorphism Level**	**Mean**	**Std Dev.**
Male	Hedonic	Low	4.08	1.86
		High	4.43	1.70
	Utilitarian	Low	4.44	1.68
		High	4.02	1.80
Female	Hedonic	Low	4.83	1.52
		High	4.15	1.79
	Utilitarian	Low	4.15	1.74
		High	3.99	1.72
Total			4.25	1.74

Table 4.12: *Between-Subjects Effects of Independent and Covariate Variables on Usage Intention*

Variables	Usage Intention		
	F Statistic	**Sig.**	η_p^2
Mood	10.924	.001	.018
Anthropomorphism level	2.781	.096	.005
AI gender	0.039	.844	.000
Purchase type	2.665	.103	.004
AI gender * purchase type	2.048	.153	.003
AI gender * anthropomorphism level	2.284	.131	.004
Purchase type * anthropomorphism level	0.092	.762	.000
AI gender * purchase type * anthropomorphism level	5.066	.025	.008

Interpretation of this three-way ANCOVA found that participants' overall mood at the time of the experiment did have a significant effect (F = 10.924, p = .001, η_p^2 = .018) on their usage intention. Individually, participants' perceptions of purchase type, AI gender, and anthropomorphism level were shown to have no significant effect on their usage intention (anthropomorphism level: F = 2.781, p = .096, η_p^2 = .005; AI gender: F = 0.039, p = .844, η_p^2

= .000; and purchase type: F = 2.665, p = .103, η_p^2 = .004). However, Hypothesis 1a was supported, as the interaction between purchase type, AI gender, and anthropomorphism level had a significant effect on usage intention (F = 5.066, p = .025, η_p^2 = .008). This empirical evidence suggests that the interaction effects of purchase type, AI gender, and anthropomorphism level had a significant impact on individuals' usage intention (behavioural response).

4.6.2 H1b: Purchase Type, Artificial Intelligence Gender, and Anthropomorphism Level, will have a Direct Effect on Participants' Purchase Intentions

Hypothesis 1b proposed that the interaction of purchase type, AI gender, and anthropomorphism level, would directly affect participants' purchase intention via AI. To test this hypothesis, a three-way ANCOVA analysis was run. The three independent variables and one covariate ("users' overall mood") were tested to understand their effects on participants' purchase intentions via AI. Results of this analysis are presented in Tables 4.13 and 4.14.

Table 4.13: *Participants' Perceived Website Purchase Intention via AI Across Experimental Conditions*

Hypothesis Variables			**Purchase Intention**	
AI Gender	**Purchase Type**	**Anthropomorphism Level**	**Mean**	**Std Dev.**
Male	Hedonic	Low	4.17	1.83
		High	4.58	1.73
	Utilitarian	Low	4.52	1.75
		High	4.36	1.83
Female	Hedonic	Low	5.00	1.53
		High	4.41	1.83
	Utilitarian	Low	4.31	1.88
		High	4.14	1.89
Total			4.43	1.80

Table 4.14: *Between-Subjects Effects of Independent and Covariate Variables on Purchase Intention*

Variable	**Purchase Intention**		
	F Statistic	**Sig.**	$\boldsymbol{\eta_p^2}$
Mood	14.182	.000	.023
Anthropomorphism level	0.817	.366	.001
AI gender	0.102	.750	.000
Purchase type	2.177	.141	.004
AI gender * purchase type	3.766	.053	.006
AI gender * anthropomorphism level	3.542	.060	.006
Purchase type * anthropomorphism level	0.014	.905	.000
AI gender * purchase type * anthropomorphism level	2.801	.095	.005

Interpretation of this three-way ANCOVA analysis found that a participant's overall mood at the time of the experiment had a significant effect (F = 14.182, p = .000, η_p^2 = .023) on the dependent variable and their purchase intention. However, an individual's perception of purchase type, AI gender, and anthropomorphism level, were found to have no significant effect on their purchase intention when analysed independently (anthropomorphism level: F = 0.817, p = .366, η_p^2 = .001; AI gender: F = 0.102, p = .750, η_p^2 = .000; and purchase type: F = 2.177, p = .141, η_p^2 = .004). Hypothesis 1b was not supported, as the interaction between purchase type, AI gender, and anthropomorphism level had no significant effect on an individual's purchase intention (F = 2.801, p = .095, η_p^2 = .005). However, the interaction of purchase type and AI gender (F = 3.766, p = .053, η_p^2 = .006), and anthropomorphism level and AI gender (F = 3.542, p = .060, η_p^2 = .006), were both very close to being significant. Future research may benefit from delving further into this topic to understand how AI development knowledge can be further influenced to understand the impacts on purchase intention. Overall, this empirical evidence suggests that the interaction effects of purchase type, AI gender, and anthropomorphism level, had no influence on an individual's purchase intention.

4.6.3 H2a: Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' website credibility response.

Hypothesis 2a proposed that the interaction of purchase type, AI gender, and anthropomorphism level, would affect participants' perception of the credibility of the website. To examine this hypothesis, three independent variables were used as fixed factors in a 2 x 2 x 2 three-way ANCOVA analysis. Participants' overall mood before beginning the experiment was included as a covariate to control for any further effects of their overall mood at the time of the experiment. The results of this analysis are presented in Tables 4.15 and 4.16.

Table 4.15: *Participants' Perceived AI Website Credibility Across Experimental Conditions*

Hypothesis Variables			Credibility	
AI Gender	**Purchase Type**	**Anthropomorphism Level**	**Mean**	**Std Dev.**
Male	Hedonic	Low	5.79	1.19
		High	5.82	0.96
	Utilitarian	Low	5.87	0.91
		High	5.68	1.08
Female	Hedonic	Low	5.80	0.89
		High	5.35	1.38
	Utilitarian	Low	5.56	1.11
		High	5.76	0.91
Total			5.70	1.08

Table 4.16: *Between-Subjects Effects of Independent and Covariate Variables on Website Credibility*

Variable	Credibility		
	F Statistic	**Sig.**	η_p^2
Mood	17.304	.000	.028
Anthropomorphism level	1.461	.227	.002
AI gender	4.572	.033	.008
Purchase type	0.061	.804	.000
AI gender * purchase type	0.414	.520	.001
AI gender * anthropomorphism level	0.158	.692	.000
Purchase type * anthropomorphism level	2.007	.157	.003
AI gender * purchase type * anthropomorphism level	5.914	.015	.010

Interpretation of this three-way ANCOVA found that a participant's overall mood at the time of the experiment had a significant effect (F = 17.304, p = .000, η_p^2 = .028) on the dependent variable (participants' "perceived credibility of the website"). Furthermore, it was found that AI gender had a significant effect (F = 4.572, p = .033, η_p^2 = .008) on the individual's perception of website credibility. This small significance indicated that male AI ($\bar{x}$ = 5.64) was perceived as slightly more credible than female AI ($\bar{x}$ = 5.46). An individual's perception of purchase type and AI anthropomorphism level were shown to have no effect on their interpretation of the credibility of the website (anthropomorphism level: F = 1.336, p = .248, η_p^2 = .002; and purchase type: F = 0.073, p = .787, η_p^2 = .000). However, Hypothesis 2a was supported, as the interaction between purchase type, AI gender, and anthropomorphism level had a significant effect on an individual's perception of AI website credibility (F = 5.914, p = .015, η_p^2 = .010). This empirical evidence supports Hypothesis 2a, as the interaction effects of purchase type, AI gender, and anthropomorphism level, had a significant impact on individuals' perceptions of the credibility of the website.

4.6.4 H2b: Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' website believability response.

Hypothesis 2b proposed that the interaction of purchase type, AI gender, and anthropomorphism level, would affect participants' perceptions of the believability of a website. To test this hypothesis, a three-way ANCOVA analysis was run. The three independent variables and covariate ("users' overall mood") were tested to understand their effects on participants' perceptions of the believability of the website. Results of this analysis are presented in Tables 4.17 and 4.18.

Table 4.17: *Participants' Perceived AI Website Believability Across Experimental Conditions*

Hypothesis Variables			Believability	
AI Gender	**Purchase Type**	**Anthropomorphism Level**	**Mean**	**Std Dev.**
Male	Hedonic	Low	5.38	1.17
		High	5.70	0.87
	Utilitarian	Low	5.67	0.90
		High	5.30	1.08
Female	Hedonic	Low	5.63	0.93
		High	5.23	1.18
	Utilitarian	Low	5.34	1.02
		High	5.42	1.00
Total			5.46	1.03

Table 4.18: *Between-Subjects Effects of Independent and Covariate Variables on Website Believability*

Variable	Believability		
	F Statistic	**Sig.**	$\boldsymbol{\eta_p^2}$
Mood	32.247	.000	.051
Anthropomorphism level	1.359	.244	.002
AI gender	2.186	.140	.004
Purchase type	0.564	.453	.001
AI gender * purchase type	0.002	.968	.000
AI Gender * anthropomorphism level	1.035	.309	.002
Purchase type * anthropomorphism level	0.198	.656	.000
AI gender * purchase type * anthropomorphism level	12.385	.000	.020

Interpretation of the three-way ANCOVA analysis found that a participant's overall mood at the time of the experiment had a significant effect (F = 32.247, p = .000, η_p^2 = .051) on the dependent variable (participants' "perceived believability of the website"). Perceptions of each independent variable (purchase type, AI gender, and anthropomorphism level) were shown to have no effect on their interpretation of the believability of the website (anthropomorphism level: F = 1.359, p = .244, η_p^2 = .002; AI gender: F = 2.186, p = .140, η_p^2 = .004; and purchase type: F = 0.564, p = .453, η_p^2 = .001). However, Hypothesis 1c was supported, as the interaction between purchase type, AI gender, and anthropomorphism level had a significant effect on perceptions of AI website believability (F = 12.385, p = .000, η_p^2 = .020). This empirical evidence supports Hypothesis 2b, as the interaction effects of purchase type, AI gender, and anthropomorphism level, had a significant impact on perceptions of the believability of the website.

4.6.5 *H2c: Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' website sense of presence response.*

Hypothesis 3c proposed that the interaction of purchase type, AI gender, and anthropomorphism level, would affect participants' sense of presence on an AI website. To test this hypothesis, a three-way ANCOVA analysis was run. The three independent variables and covariate ("users' overall mood") were tested to understand their effects on participants' sense of presence. Results of this analysis are presented in Tables 4.19 and 4.20.

Table 4.19: *Participants' Perceived AI Website Sense of Presence Across Experimental Conditions*

Hypothesis Variables			Sense of Presence	
AI Gender	**Purchase Type**	**Anthropomorphism Level**	**Mean**	**Std Dev.**
Male	Hedonic	Low	5.07	1.52
		High	5.01	1.47
	Utilitarian	Low	4.88	1.54
		High	4.85	1.52
Female	Hedonic	Low	5.19	1.38
		High	4.72	1.49
	Utilitarian	Low	4.97	1.48
		High	4.75	1.63
Total			4.92	1.51

Table 4.20: *Between-Subjects Effects of Independent and Covariate Variables on Website Sense of Presence*

Variable	Sense of Presence		
	F Statistic	**Sig.**	η_p^2
Mood	37.017	.000	.058
Anthropomorphism level	2.834	.093	.005
AI gender	0.301	.583	.001
Purchase type	1.509	.220	.003
AI gender * purchase type	0.065	.799	.000
AI gender * anthropomorphism level	2.277	.132	.004
Purchase type * anthropomorphism level	0.733	.392	.001
AI gender * purchase type * anthropomorphism level	0.111	.739	.000

Interpretation of this three-way ANCOVA analysis found that a participant's overall mood at the time of the experiment had a significant effect (F = 37.017, p = .000, η_p^2 = .058) on the dependent variable ("perception of sense of presence on the website"). Individuals' perception of purchase type, AI gender, and anthropomorphism level, was shown to have no effect on their perception of sense of presence on the website (anthropomorphism level: F = 2.834, p = .093, η_p^2 = .005; AI gender: F = 0.301, p = .583, η_p^2 = .001; and purchase type: F = 1.509, p = .220, η_p^2 = .003). Hypothesis 2c was not supported, as the interaction between purchase type, AI gender, and anthropomorphism level had no significant effect on perceptions of a sense of presence on the website (F = 0.111, p = .739, η_p^2 = .000). Overall, this empirical evidence suggests that the interaction effects of purchase type, AI gender, and anthropomorphism level, had no influence on perceptions of a sense of presence on the website.

4.6.6 H2d: Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' website involvement response.

Hypothesis 2d proposed that the interaction of purchase type, AI gender, and anthropomorphism level, would affect participants' involvement with a website. To test this hypothesis, a three-way ANCOVA analysis was run. The three independent variables and covariate ("users' overall mood") were tested to understand their effects on participants' involvement. Results of this analysis are presented in Tables 4.21 and 4.22.

Table 4.21: *Participants' Perceived AI Website Involvement Across Experimental Conditions*

Hypothesis Variables			Involvement	
AI Gender	**Purchase Type**	**Anthropomorphism Level**	**Mean**	**Std Dev**
Male	Hedonic	Low	5.39	1.44
		High	5.57	1.07
	Utilitarian	Low	5.46	1.24
		High	5.33	1.38
Female	Hedonic	Low	5.64	1.09
		High	5.42	1.15
	Utilitarian	Low	5.39	1.41
		High	5.17	1.46
Total			5.42	1.29

Table 4.22: *Between-Subjects Effects of Independent and Covariate Variables on Website Involvement*

Variable	Involvement		
	F Statistic	**Sig.**	$\boldsymbol{\eta_p^2}$
Mood	27.807	.000	.044
Anthropomorphism level	0.960	.328	.002
AI gender	0.209	.648	.000
Purchase type	2.810	.094	.005
AI gender * purchase type	0.771	.380	.001
AI gender * anthropomorphism level	2.003	.157	.003
Purchase type * anthropomorphism level	0.296	.587	.000
AI gender * purchase type * anthropomorphism level	0.453	.501	.001

Interpretation of the three-way ANCOVA analysis found that a participant's overall mood had a significant effect (F = 27.807, p = .000, η_p^2 = .044) on the dependent variable ("website involvement"). Perceptions of purchase type, AI gender, and anthropomorphism level, were shown to have no effect on participants' involvement with the website (anthropomorphism level: F = 0.960, p = .328, η_p^2 = .002; AI gender: F = 0.209, p = .648, η_p^2 = .000; and purchase type: F = 2.810, p = .094, η_p^2 = .005). Hypothesis 2d was not supported, as the interaction between purchase type, AI gender, and anthropomorphism level had no significant effect on perceptions of AI website involvement (F = 0.453, p = .501, η_p^2 = .001). Overall, this empirical evidence suggests that the interaction effects of purchase type, AI gender, and anthropomorphism level, had no influence on participants' website involvement.

4.6.7 H2e: Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' technology helpfulness response.

Hypothesis 2e proposed that the interaction of purchase type, AI gender, and anthropomorphism level, would affect participants' perceived helpfulness of an AI website. To test this hypothesis, a three-way ANCOVA analysis was run. The three independent variables and covariate ("users' overall mood") were tested to understand their effects on participants' perceptions of helpfulness. Results of this analysis are presented in Tables 4.23 and 4.24.

Table 4.23: *Participants' Perceived AI Website Helpfulness Across Experimental Conditions*

Hypothesis Variables			Helpfulness	
AI Gender	**Purchase Type**	**Anthropomorphism Level**	**Mean**	**Std Dev**
Male	Hedonic	Low	5.51	1.42
		High	5.73	1.10
	Utilitarian	Low	5.61	0.92
		High	5.53	1.12
Female	Hedonic	Low	5.57	1.27
		High	5.41	1.37
	Utilitarian	Low	5.53	1.22
		High	5.36	1.27
Total			5.53	1.22

Table 4.24: *Between-Subjects Effects of Independent and Covariate Variables on Technology Helpfulness*

Variable	Helpfulness		
	F Statistic	**Sig.**	η_p^2
Mood	14.473	.000	.023
Anthropomorphism level	0.236	.627	.000
AI gender	1.874	.172	.003
Purchase type	0.269	.604	.000
AI gender * purchase type	0.000	.991	.000
AI gender * anthropomorphism level	1.788	.182	.003
Purchase type * anthropomorphism level	0.400	.527	.001
AI gender * purchase type * anthropomorphism level	0.467	.495	.001

Interpretation of the three-way ANCOVA and independent t-test analysis found that a participant's overall mood at the time of the experiment had a significant effect (F = 14.473, p = .000, η_p^2 = .023) on the dependent variable (participants' "perception of the helpfulness of the website"). Perceptions of purchase type, AI gender, and anthropomorphism level, were shown to have no effect on perceptions of the helpfulness of the website (anthropomorphism level: F = 0.236, p = .627, η_p^2 = .000; AI gender: F = 1.874, p = .172, η_p^2 = .003; and purchase type: F = 0.269, p = .604, η_p^2 = .000). Hypothesis 2e was not supported, as the interaction between purchase type, AI gender, and anthropomorphism level had no significant effect on an individual's perception of website helpfulness (F = 0.467, p = .495, η_p^2 = .001). Overall, this empirical evidence suggests that the interaction effects of purchase type, AI gender, and anthropomorphism level, had no influence on perceptions of technology helpfulness.

4.6.8 H3: Cognitive Responses will have an effect on participants' AI usage intention, and purchase intention.

Two linear regression analyses were performed to identify how a participants response to each of the five cognitive responses could be used to predict their usage and purchase intentions. The results of both regression analyses are presented in Tables 4.25, 4.26, and 4.27.

The first linear regression analysis was conducted to determine how the five cognitive responses could be used to predict participants usage intention responses. The results discovered that four of the five cognitive responses did significantly predict their usage intentions, R^2 =.597, (F(5, 606) = 179.333, p < .05). The four significant cognitive responses explained 59.7% of the variance in usage intention. The second linear regression analysis was conducted to determine how the five cognitive responses could be used to predict participants purchase intention responses. The results discovered that four of the five cognitive responses did significantly predict their purchase intentions, R^2 = .583 (F(5, 606) = 169.179, p < .05). The four significant cognitive responses explained 58.3% of the variance in purchase intention.

To test the acceptability of the analyses, collinearity statistics were measured. This test looks at the VIF and tolerance statistics, which are used to inform how strong the relationship between each predictor variables (cognitive responses) are when compared to the other predictor variables. Field (2013) states a VIF below 10 and a tolerance statistic above 0.2 indicated a strong relationship. The results within this analysis identified VIF values between 2.450 and 4.709, and tolerance statistics between .212 and .408, therefore confirming that the predictor variables used within this analysis have a strong positive relationship. Next, these analyses were tested using the Durbin Watson test, which is used to determine whether the adjacent residuals are correlated. A value of 2 represents a uncorrelated residual, and a value of below 2 indicating a positive correlation (Field, 2013). The Durbin Watson statistic from the first analysis was 1.647, while the second analysis was 1.502, meaning both analyses indicated a positive correlation between errors. Lastly, the P-Plot of both tests were analysed, it was identified that both models achieved a normal P-Plot of regressions standardised residual.

Table 4.25: *Cognitive Response Perception Effect on Purchase and Usage Intention - Linear Regression Model Summary*

Model	R	R Squared	Adjusted R Squared	Std. Error of the Estimate	Durbin-Watson
Model 1 (Usage Intention)	.772	.597	.593	1.11	1.647
Model 2 (Purchase Intention)	.763	.583	.579	1.17	1.502

Table 4.26: *Cognitive Response Effect on Purchase and Usage Intention - Linear Regression Model Analysis*

Model		Sum of Squares	df	Mean Squares	F statistic	Sig.
Model 1 (Usage Intention)	Regression	1107.886	5	221.577	179.333	.000
	Residual	748.752	606	1.236		
	Total	1856.638	611			
Model 2 (Purchase Intention)	Regression	1154.417	5	230.883	169.179	.000
	Residual	827.024	606	1.365		
	Total	1981.441	611			

Table 4.27: *Cognitive Response Effect on Purchase and Usage Intention - Linear Regression Coefficients Analysis*

Model		Unstandardised Coefficients		Standardised Coefficients Beta	T-test	Sig.	Collinearity Statistics	
		B	Std. Error				Tolerance	VIF
Model 1 (Usage Intention)	(Constant)	-2.626	.263		-9.968	.000		
	Website Credibility	-.036	.080	-.022	-.447	.655	.274	3.655
	Website Believability	.418	.094	.248	4.431	.000	.212	4.709
	Website Sense of Presence	.168	.048	.146	3.534	.000	.392	2.551
	Website Involvement	.149	.058	.110	2.583	.010	.365	2.738
	Technology Helpfulness	.573	.058	.399	9.894	.000	.408	2.450
Model 2 (Purchase Intention)	(Constant)	-2.600	.277		-9.391	.000		
	Website Credibility	-.115	.084	-.068	-1.364	.173	.274	3.655
	Website Believability	.522	.099	.300	5.263	.000	.212	4.709
	Website Sense of Presence	.141	.050	.118	2.809	.005	.392	2.551
	Website Involvement	.232	.061	.166	3.827	.000	.365	2.738
	Technology Helpfulness	.522	.061	.353	8.582	.000	.408	2.450

4.6.8.1 H3a: Website credibility response will have an effect on participants' AI usage intention, and Purchase Intention.

The purpose of H3a was to predict how participants' usage and purchase intentions were impacted based on their perceptions of website credibility, two analyses were conducted to create this prediction. The first linear regression analysis was conducted to determine if a participants perception of "website credibility" could predict their "AI usage intention" response. The results discovered that a participants' website credibility perception did not significantly predict their usage intention based on the findings (β = -.036, t = -.447, p = .655). The second linear regression analysis was conducted to determine if a participants perception of "website credibility" could predict their "AI purchase intention" response. The results discovered that a participants' website credibility perception did not significantly predict their purchase intention (β = -.115, t = -1.364, p = .173).

Based on the evidence from these two analyses, Hypothesis 3a was not supported, as participants' perceptions of website credibility was not shown to predict their usage and purchase intentions.

4.6.8.2 H3b: Website believability response will have an effect on participants' AI usage intention, and purchase intention.

The purpose of H3b was to predict how participants' usage and purchase intentions were impacted based on their perceptions of website believability, two analyses were conducted to create this prediction. The first linear regression analysis was conducted to determine if a participants perception of "website believability" could predict their "AI usage intention" response. The results discovered that a participants' website believability perception did significantly predict their usage intention (β = .418, t = 4.431, p = .000). The second linear regression analysis was conducted to determine if a participants perception of "website believability" could predict their "AI purchase intention" response. The results discovered that a participants' website believability perception did significantly predict their purchase intention based on the findings (β = .522, t = 5.263, p = .000).

Based on the evidence from these two analyses, Hypothesis 3b was supported, as participants' perceptions of website believability was shown to predict their usage and purchase intentions.

4.6.8.3 H3c: Website sense of presence response will have an effect on participants' AI usage intention, and purchase intention.

The purpose of H3c was to predict how participants' usage and purchase intentions were impacted based on their perceptions of website sense of presence, two analyses were conducted to create this prediction. The first linear regression analysis was conducted to determine if a participants perception of "website sense of presence" could predict their "AI usage intention" response. The results discovered that a participants' website sense of presence perception did significantly predict their usage intention based on the findings (β = .168, t = 3.534, p = .000). The second linear regression analysis was conducted to determine if a participants perception of "website sense of presence" could predict their "AI purchase intention" response. The results discovered that a participants' website sense of presence perception did significantly predict their purchase intention based on the findings (β = .141, t = 2.809, p = .005).

Based on the evidence from these two analyses, Hypothesis 3c was supported, as participants' perceptions of website sense of presence was shown to predict their usage and purchase intentions.

4.6.8.4 H3d: Website involvement response will have an effect on participants' AI usage intention, and purchase intention.

The purpose of H3d was to predict how participants' usage and purchase intentions were impacted based on their perceptions of website involvement, two analyses were conducted to create this prediction. The first linear regression analysis was conducted to determine if a participants perception of "website involvement" could predict their "AI usage intention" response. The results discovered that a participants' website involvement perception did significantly predict their usage intention based on the findings (β = .149, t = 2.583, p = .010). The second linear regression analysis was conducted to determine if a participants perception of "website involvement" could predict their "AI purchase intention" response. The results discovered that a participants' website involvement perception did significantly predict their purchase intention based on the findings (β = .232, t = 3.827, p = .000).

Based on the evidence from these two analyses, Hypothesis 3d was supported, as participants' perceptions of website involvement was shown to predict their usage and purchase intentions.

4.6.8.5 H3e: Technology helpfulness response will have an effect on participants' AI usage intention, and purchase intention.

The purpose of H3e was to predict how participants' usage and purchase intentions were impacted based on their perceptions of technology helpfulness, two analyses were conducted to create this prediction. The first linear regression analysis was conducted to determine if a participants perception of "technology helpfulness" could predict their "AI usage intention" response. The results discovered that a participants' technology helpfulness perception did significantly predict their usage intention based on the findings (β = .573, t = 9.894, p = .000). The second linear regression analysis was conducted to determine if a participants perception of "technology helpfulness" could predict their "AI purchase intention" response. The results discovered that a participants' technology helpfulness perception did significantly predict their purchase intention based on the findings (β = .522, t = 8.582, p = .000).

Based on the evidence from these two analyses, Hypothesis 3e was supported, as participants' perceptions of technology helpfulness was shown to predict their usage and purchase intentions.

4.7 Hypotheses Results

Table 4.28: *Hypotheses Testing Results*

No.	Research Hypotheses	Supported?
H1a	Purchase type, and artificial intelligence gender and anthropomorphism level, will have a direct effect on participants' usage intentions	Yes
H1b	Purchase type, and artificial intelligence gender, and anthropomorphism level, will have a direct effect on participants' purchase intention via AI	No
H2a	Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' website credibility response.	Yes
H2b	Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' website believability response.	Yes
H2c	Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' website sense of presence response.	No
H2d	Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' website involvement response.	No
H2e	Purchase type, and artificial intelligence gender and anthropomorphism level, will have an effect on participants' technology helpfulness response.	No
H3a	Website credibility response will have an effect on participants' AI usage intention, and purchase intention.	No
H3b	Website believability response will have an effect on participants' AI usage intention, and purchase intention.	Yes
H3c	Website sense of presence response will have an effect on participants' AI usage intention, and purchase intention.	Yes
H3d	Website involvement response will have an effect on participants' AI usage intention, and purchase intention.	Yes
H3e	Technology helpfulness response will have an effect on participants' AI usage intention, and purchase intention.	Yes

The following section re-tested all twelve hypotheses using a Structural Equation Model (SEM), this was done to understand the overall effect of all variables when interpreted at once, rather than individually, to create a more in depth analyses of all hypotheses. Understanding the effect of all variables at once is necessary, as participants were subjected to the whole experimental stimuli at the same time. Therefore, understanding the effect of all variables at the same time is vitally important.

4.8 Structural Equation Modelling

4.8.1 Structural Equation Modelling Approach

The use of SEM has become the norm in both marketing, tourism and information system studies to test the relationship between several independent and dependent variables. In relation to technology use and acceptance, several studies use (Joo & Sohn, 2008; Lin, 2007) the technique. This SEM builds upon the twelve hypotheses findings, by understanding how participants were affected simultaneously by all variables, to further ascertain the findings of this thesis. SEM was required as ANCOVA does not explain which condition accounts for the largest significance in mean difference (Sahoo et al., 2016). Therefore this study utilised a SEM and ANCOVA analysis to answer and confirm the twelve hypotheses, for any difference in significance the SEM results will be used to frame the hypotheses discussion due to the suitability of the method. This study utilised SPSS 26 for exploratory factor analysis, and SmartPLS 3 to develop the structural equation model. This study utilised SEM to investigate various aspects of AI against participant satisfaction, the model follows a two-step approach consisting of the measurement model and testing the structural model (Anderson & Gerbing, 1988). In PLS-SEM these are known as outer and inner model assessment respectively (Hair Jr et al., 2014).

4.8.2 Measurement Model (Outer Model Assessment)

To understand the psychometric properties of each scale within this study, a ten-factor measurement model was created using SmartPLS 3. To attest the model's validity and reliability a number of criteria were assessed, including Cronbach's alpha, Average Variance Extracted (AVE), Composite Reliability (CR), and Standardised Loadings (Table 4.29). Nunnally and Bernstein (1994) stated that standardised loading are required to be above 0.7 to be valid, within this model all standardised loadings were above 0.87. All Cronbach's alpha were above 0.91, well above the minimum threshold of 0.7 as stated by Nunally (1978), which means all items and constructs were internally consistent. Fornell and Larcker (1981) identified that an AVE result above 0.50 was required for the scales convergent validity, all AVE results were found to be above 0.82. Lastly, a CR above 0.7 was required, as identified by Fornell and Larcker (1981), all CR's within this study were above 0.94. The Fornell and Larcker's (1981) method was utilised within Table 4.30, to identify and explain the models discriminant validity. A positive outcome of this method requires all square root AVE of each construct to be greater than the correlations between the construct and the remaining constructs within the model. The results presented in Table 4.29 and 4.30 conclude and confirm the suitability of the SEM within this thesis.

Table 4.29: *SEM construct and item psychometric properties*

Items	**Std. Loadings**	**Crona**	**CR**	**AVE**	Q^2
AI Gender		**0.989**	**0.991**	**0.965**	
I considered the AI to be Masculine.	0.985				
I considered the AI to be Feminine.	0.978				
The voice I experienced on the website sounded like a male voice.	0.988				
The voice I experiences on the website sounded like a female voice.	0.978				
Purchase type		**0.970**	**0.976**	**0.870**	
Not Fun/Fun.	0.942				
Dull/Exciting.	0.944				
Not Delightful/Delightful.	0.954				
Not Thrilling/Thrilling.	0.903				
Not Enjoyable/Enjoyable.	0.929				
Tedious/Stimulating.	0.924				
Anthropomorphism Level		**0.963**	**0.973**	**0.899**	
Machine-like/human-like.	0.947				
Artificial/natural.	0.950				
Not life-like/life-like.	0.945				
Robotic/human.	0.951				

Credibility		**0.953**	**0.969**	**0.913**	**0.135**
This scenario was realistic.	0.946				
This scenario was credible.	0.961				
This scenario was believable.	0.960				
Believability		**0.947**	**0.959**	**0.825**	**0.165**
The experience was believable.	0.902				
The experience was trustworthy.	0.881				
The experience was Credible.	0.942				
The experience was Reasonable.	0.913				
The experience was Convincing.	0.901				
Sense of Presence		**0.949**	**0.967**	**0.907**	**0.210**
Your sense of presence was strong while watching Ryan's Travel's AI video.	0.953				
Your sense of 'being there' was strong while watching Ryan's Travel's AI video.	0.959				
Your sense of inclusion was strong while watching Ryan's Travel's AI video.	0.945				
Involvement		**0.918**	**0.948**	**0.859**	**0.213**
Not involved at all/Very involved.	0.896				
Not interested at all/Very interested.	0.931				
Not engaged at all/Very engaged.	0.954				
Helpfulness		**0.937**	**0.960**	**0.889**	**0.231**
The AI was Informative.	0.909				
The AI was Useful.	0.956				
The AI was Helpful.	0.963				
Usage Intention		**0.976**	**0.984**	**0.955**	**0.603**
If given a chance, I think I'll use this software in the near future.	0.973				

If given a chance, I'm certain to use this software in the near future.	0.978				
If given a chance, I plan to use the software during the near future.	0.980				
Purchase Intention		**0.955**	**0.968**	**0.883**	**0.540**
How likely is it that you would return to Ryan's Travel's website?	0.961				
How likely is it that you would consider using Ryan's Travel's services in the short term? (within the next 3 months).	0.878				
How likely is it that you would consider using Ryan's Travel's services in the longer term? (within the next year).	0.961				
For the purchase used in this example, how likely is it that you would user Ryan's Travel's services?	0.955				

Table 4.30: *Discriminant validity using Fornell and Larcker Method.*

Constructs	AI Gender	Purchase Type	Anthro Level	Credibility	Believability	Sense of Presence	Involvement	Helpfulness	Purchase Intention	Usage Intention
AI Gender	**0.982**									
Purchase Type	-0.011	**0.933**								
Anthro Level	0.096	0.337	**0.948**							
Credibility	0.090	0.314	0.312	**0.956**						
Believability	0.068	0.350	0.384	0.870	**0.908**					
Sense of Presence	0.018	0.385	0.408	0.504	0.578	**0.952**				
Involvement	0.011	0.430	0.393	0.508	0.572	0.751	**0.927**			
Helpfulness	0.051	0.445	0.390	0.598	0.689	0.620	0.673	**0.943**		
Purchase Intention	-0.006	0.460	0.470	0.544	0.652	0.607	0.708	0.708	**0.939**	
Usage Intention	-0.006	0.474	0.497	0.558	0.652	0.613	0.723	0.723	0.922	**0.977**

4.8.3 Structural Model Evaluation (Inner Model Assessment)

Following the PLS algorithm analysis, a bootstrapping analysis (n=5000) was conducted. The R^2 values (shown in Figure 4.1) identified that AI gender, purchase type, anthropomorphism level and the five cognitive responses explained 64% of the total variance in usage intention and 62.1% of the total variance in purchase intention. The bootstrapped path coefficients (Table 4.31 and Figure 4.1) found that AI gender (β = -0.056, p < 0.026), purchase type (β = 0.114, p < 0.000), and anthropomorphism level (β = 0.176, p < 0.000), had a significant relationship with participants usage intention, thus supporting H1a. Contradictory to the results found in section 4.6.2, H1b was found to be supported through the SEM. It was discovered that AI Gender (β = -0.050, p < 0.042), purchase type (β = 0.104, p < 0.002), and anthropomorphism level (β = 0.143, p < 0.000), had a significant relationship with participants purchase intention, thus supporting H1b.

AI gender, purchase type, and anthropomorphism level were found to explain, 15.1% of the total variance in website credibility, 20.4% of the total variance in website believability, 23.6% of the total variance in website sense of presence, 25.4% of the total variance in website involvement, and 26.4% of the total variance in technology helpfulness. The bootstrapped analysis supported H2a (AI gender: β = 0.070, p < 0.046, purchase type: β = 0.239, p < 0.000, and anthropomorphism level: β = 0.225, p < 0.000). However, the analysis rejected H2b, H2c, H2d, and H2e, all four were rejected due to non-significant relationship with AI gender.

The final outcome of the bootstrap path coefficient analysis looked at the third hypothesis stream, to understand how each of the five cognitive responses effected participants behavioural responses. Website credibility was discovered to have non-significant relationship with participants behavioural response, as usage intention (β = -0.022, p < 0.690), and purchase intention (β = -0.086, p < 0.127) were both found to be non-significant, therefore rejecting H3a. Website believability was found to have a significant relationship with participants behavioural responses, as usage intention (β = 0.220, p < 0.001), and purchase intention (β = 0.297, p < 0.000) were discovered to be significant, therefore supporting H3b. Website sense of presence was found to have a significant relationship with participants behavioural responses, as usage intention (β = 0.111, p < 0.006), and purchase intention (β = 0.089, p < 0.038) were discovered to be significant, therefore supporting H3c.

Website involvement was found to have no relationship with participants behavioural responses, as usage intention (β = 0.071, $p < 0.071$), and purchase intention (β = 0.135, $p < 0.001$) were found to have no path relationship, therefore rejecting H3d. Lastly, technology helpfulness was found to have a relationship with participants behavioural response, as usage intention (β = 0.352, $p < 0.000$), and purchase intention (β = 0.309, $p < 0.000$) were discovered to be significant, therefore supporting H3e.

The findings of the SEM were slightly contradictory from the original ANCOVA and linear regression analysis conducted earlier within the chapter. Hypothesis H1b was supported by the SEM, opposing the results identified from the ANCOVA analysis, while H2b and H3d were not supported by the SEM results in contrast to the significant results found through the three-way ANCOVA and linear regression analyses in Section 4.6. The main reason for the contradictory results is because a SEM analysis looks at understanding the effect of all latent variables at once, to understand how certain variables had larger effects than others. Whereas the original three-way ANCOVA and linear regression analyses looked only at the individual variables involved within each hypothesis.

All variables were found to have a significant effect size, with all Q^2 results found to be above 0.1, with the effect size of purchase and usage intention found to both be above 0.5 indicating a large effect.

Figure 4.1: *PLS Path Model* (Note. Values in blue circles represent $\mathbf{R^2}$ value)

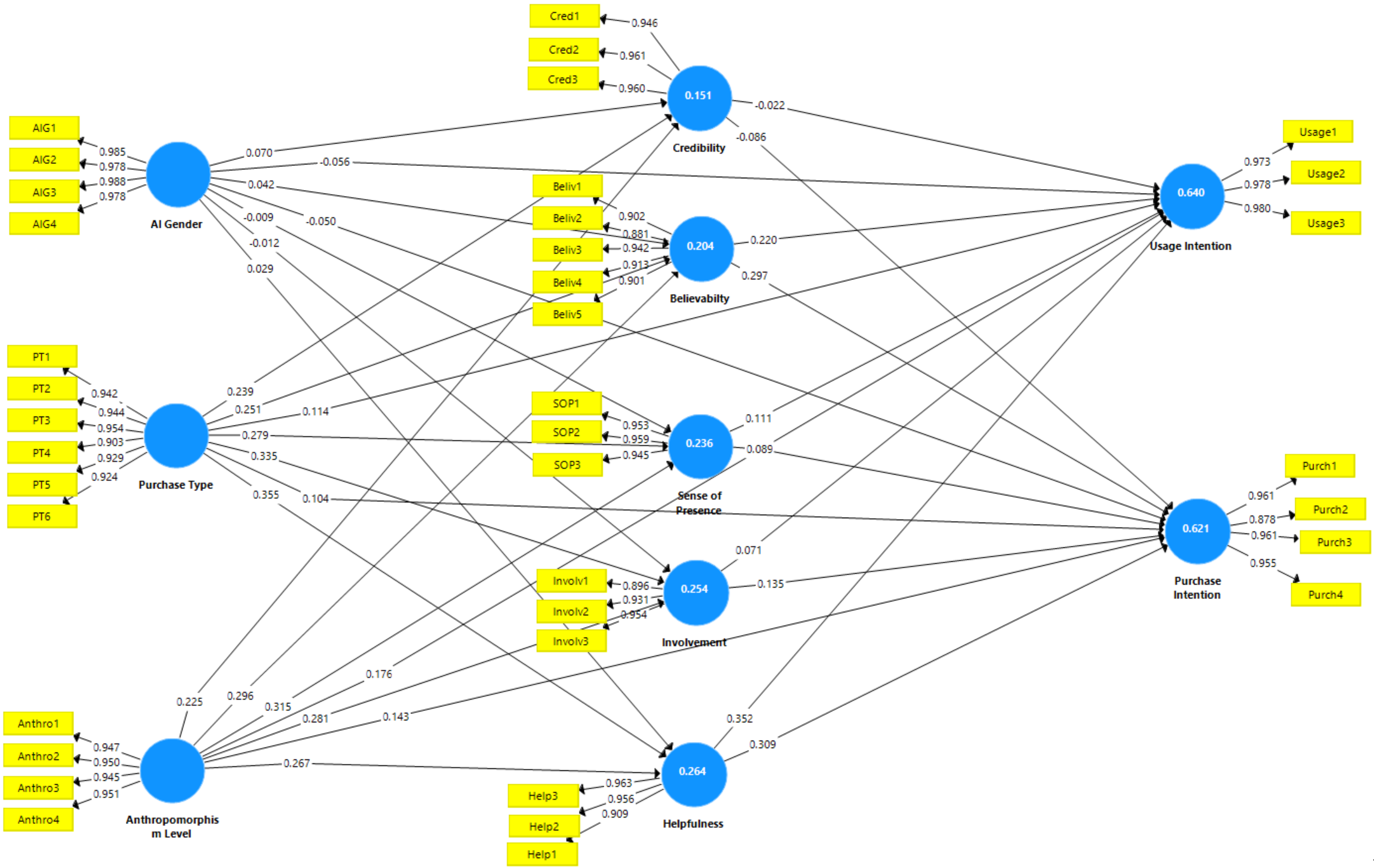


Table 4.31: *Path coefficients, size effects and hypotheses results*

Hypothesis	Paths	Std. Path Coeff. (β)	t-statistic	p-value	Supported?
H1a	AI Gender → Usage Intention	-0.056	2.227	0.026	
	Purchase Type → Usage Intention	0.114	3.553	0.000	Yes
	Anthropomorphism Level → Usage Intention	0.176	6.010	0.000	
H1b	AI Gender → Purchase Intention	-0.050	2.039	0.042	
	Purchase Type → Purchase Intention	0.104	3.055	0.002	Yes
	Anthropomorphism Level → Purchase Intention	0.143	4.877	0.000	
H2a	AI Gender → Website Credibility	0.070	2.004	0.046	
	Purchase Type → Website Credibility	0.239	4.714	0.000	Yes
	Anthropomorphism Level → Website Credibility	0.225	5.224	0.000	
H2b	AI Gender → Website Believability	0.042	1.199	0.231	
	Purchase Type → Website Believability	0.251	5.278	0.000	No
	Anthropomorphism Level → Website Believability	0.296	8.041	0.000	
H2c	AI Gender → Sense of Presence	-0.009	0.240	0.811	
	Purchase Type → Sense of Presence	0.279	6.356	0.000	No
	Anthropomorphism Level → Sense of Presence	0.315	10.115	0.000	
H2d	AI Gender → Website Involvement	-0.012	0.337	0.736	
	Purchase Type → Website Involvement	0.335	7.901	0.000	No
	Anthropomorphism Level → Website Involvement	0.281	8.638	0.000	
H2e	AI Gender → Technology Helpfulness	0.029	0.782	0.435	
	Purchase Type → Technology Helpfulness	0.355	7.801	0.000	No
	Anthropomorphism Level → Technology Helpfulness	0.267	7.292	0.000	

H3a	Website Credibility → Usage Intention Website Credibility → Purchase Intention	-0.022 -0.086	0.400 1.528	0.690 0.127	No
H3b	Website Believability → Usage Intention Website Believability → Purchase Intention	0.220 0.297	3.472 4.595	0.001 0.000	Yes
H3c	Website Sense of Presence → Usage Intention Website Sense of Presence → Purchase Intention	0.111 0.089	2.756 2.076	0.006 0.038	Yes
H3d	Website Involvement → Usage Intention Website Involvement → Purchase Intention	0.071 0.135	1.807 3.194	0.071 0.001	No
H3e	Technology Helpfulness → Usage Intention Technology Helpfulness → Purchase Intention	0.352 0.309	8.551 7.423	0.000 0.000	Yes

4.9 Chapter Summary

Hypothesis 1a examined the interaction effects of purchase type, AI gender, and anthropomorphism levels on users' usage intentions on the AI website. The three-way ANCOVA analyses found a significant interaction between the three independent variables on "usage intention with AI." Furthermore, the analysis found that users' overall mood at the time of the experiment affected their usage intentions; the more positive they felt, the greater their usage intention increased. Hypothesis 1a was therefore supported. The SEM then further confirmed this hypothesis.

Hypothesis 1b examined the interaction effects of purchase type, AI gender, and anthropomorphism level on users' purchase intentions on the AI website. The three-way ANCOVA analysis found a non-significant interaction between the three independent variables on "purchase intention via AI." However, the analysis found that users' overall mood at the time of the experiment affected their usage intentions; the more positive they felt, the greater was their usage intention. Hypothesis 1b was therefore rejected due to a non-significant interaction between the three independent variables on participants' "purchase intention." However, the SEM overturned the rejected hypothesis, through the discovery that all three independent variables had a significant effect against participants purchase intention, identifying a positive impact. Therefore, Chapter Five will discuss the significance discovered of the three independent variables significantly effecting participants purchase intention via AI.

Hypothesis 2a and 2b examined the interaction effects of purchase type, AI gender, and anthropomorphism levels on users' perceptions of website credibility and believability. The three-way ANCOVA analysis revealed a small interaction effect between the three independent variables on users' "perception of website credibility and believability." Furthermore, it was found that users' overall mood at the time of the experiment significantly affected their perceptions of website credibility and believability. Both Hypothesis 2a and Hypothesis 2b were therefore supported. The SEM further confirmed H2a, however, H2b was discovered to be rejected within the model as AI gender was identified as having a non-significant effect on participants' website believability response.

Hypothesis 2c examined the interaction effects of purchase type, AI gender, and anthropomorphism levels on users' sense of presence with the AI website. The three-way ANCOVA analysis found no significant interaction between the three independent variables on users' "sense of presence while experiencing the AI website." However, users' overall mood at the time of the experiment was shown to affect their sense of presence. Hypothesis 2c was therefore rejected due to non-significant interactions between the three independent variables on users' "sense of presence while experiencing the AI website." The SEM then further confirmed this hypothesis.

Hypothesis 2d examined the interaction effects of purchase type, AI gender, and anthropomorphism levels on users' involvement with the AI website. The three-way ANCOVA analysis found no significant interaction between the three independent variables on users' "involvement with the website." However, the analysis found that users' overall mood at the time of the experiment affected their perceptions of how involved they felt; the more positive they felt, the greater their perceptions of involvement. Hypothesis 2d was therefore rejected due to the non-significant interaction between the three independent variables on "user involvement." The SEM then further confirmed this hypothesis.

Hypothesis 2e examined the interaction effects of purchase type, AI gender, and anthropomorphism level on users' perceptions of the helpfulness of the website and AI. The three-way ANCOVA analysis found no significant interaction between the three independent variables on users' "perceptions of AI and website helpfulness." However, users' overall mood at the time of the experiment was shown to affect their perceptions of how helpful the AI was. Hypothesis 2e was therefore rejected due to insignificant interaction between the three independent variables on users' "perceived helpfulness of the AI website." The SEM then further confirmed this finding by rejecting H2e.

Hypothesis 3a sought to understand how participants' perceptions of website credibility could predict a user's usage and purchase intentions via AI. The linear regression analysis found no significance between credibility and both usage ($p = .655$) and purchase ($p = .173$) intentions via AI. The results from the SEM further confirmed this finding, by identifying no significance between credibility on usage and purchase intention, therefore rejecting H3a.

Hypothesis 3b sought to understand how participants' perceptions of website believability could predict a user's usage and purchase intentions via AI. The linear regression analysis confirmed this hypothesis, as website believability was identified as significant in predicting both usage ($p < .005$) and purchase ($p < .005$) intention via AI. The results from the SEM further confirmed this finding.

Hypothesis 3c sought to understand how participants' sense of presence on the website could be used to predict their usage and purchase intentions via AI. The linear regression analysis confirmed this hypothesis, as website sense of presence was identified as significant in predicting both usage ($p < .005$) and purchase ($p < .005$) intention via AI. The results from the SEM further confirmed this finding.

Hypothesis 3d sought to understand how participants' involvement with the AI website could be used to predict their usage and purchase intentions via AI. The linear regression analysis confirmed this hypothesis, as website involvement was identified as significant in predicting both usage ($p < .005$) and purchase ($p < .005$) intention via AI. However, the SEM then rejected H3d, as website involvement was found to be non-significant in predicting usage intention (p-value 0.071). Therefore, the discussion will reflect the findings of the SEM over the linear regression due to its suitability at understanding the effect of all variables as a whole.

Hypothesis 3e sought to understand how participants' perceptions of website helpfulness could be used to predict their usage and purchase intentions via AI. The linear regression analysis confirmed this hypothesis, as technology helpfulness was identified as significant in predicting both usage ($p < .005$) and purchase ($p < .005$) intention via AI. The results from the SEM further confirmed this finding.

Chapter 5. Discussion and Conclusion

5.1 Introduction

This chapter summaries this research by outlining the key findings identified in Chapter 4 and what they mean in relation to previous literature and for future research. First, a summary of the three hypothesis streams is presented. This is followed by an explanation of the purpose and findings of each hypothesis, presented in conjunction with findings from the extant literature. Practical and theoretical implications are discussed, and research limitations and future research recommendations are overviewed.

5.2 Primary Research Findings

5.2.1 Summary of Research Hypotheses

5.2.1.1 Hypothesis One: Summary

The manipulation of purchase type, AI gender, and anthropomorphism level, was found to have a direct influence on participants' usage intentions, with no influence found on their purchase intentions. This finding informs future literature and AI development of the impact of manipulating various features to influence users' usage intentions, as noted in the literature. With the influence of hedonic purchases (Suparno, 2020), AI gender attractiveness (Nowak & Rauh, 2005), and high levels of anthropomorphism, required to influence users' behavioural responses (Jia et al., 2021). The majority of previous studies identified all three independent variables as having an impact on users' behavioural responses (Chaudhuri et al., 2010; Han, 2021; Jia et al., 2021; Laksmidewi et al., 2017; Tay et al., 2014). However, this research did not discover any evidence of the independent variables' manipulation or individual effects on consumers' purchase intention to the AI experiment. This may have occurred for various reasons, such as the creation limitations of the AI in this study, the manipulation of anthropomorphism not being interpreted correctly by participants, or poor time selection due to the effects of COVID-19 impacting participants' desire to plan travel during the global pandemic at the time of the study. Although the three-way ANCOVA analysis was unable to find any influence, the SEM identified that as a whole, the three independent variables did impact participants purchase intention, confirming previous findings (Chaudhuri et al., 2010; Han, 2021; Jia et al., 2021; Laksmidewi et al., 2017; Tay et al., 2014). Future research should take the next step, by creating an authentic AI travel itinerary software, to understand how the manipulation of purchase type, AI gender, and anthropomorphism level creates an influence on users' behavioural responses in a real-world setting.

5.2.1.2 Hypothesis Two: Summary

This hypothesis stream predicted that the manipulation of purchase type, AI gender, and anthropomorphism level would have an effect on participants' cognitive responses. However, this manipulation resulted in only two effects: these were on "website credibility" (H2a) and "website believability" (H2b). The cognitive responses on website sense of presence (H2c), website involvement (H2d), and technology helpfulness (H2e), were found to be unaffected by the manipulation of purchase type, AI gender, and anthropomorphism levels. In-line with previous literature, these finding informs future researchers and future AI developers, that the manipulation of purchase type (Sarkar & Sarkar, 2019; Suparno, 2020; Waytz et al., 2014), AI gender (Craciun & Moore, 2019; Tay et al., 2014), and anthropomorphism level (Nowak, 2000; Waytz et al., 2014), can influence a user's perception of an AI website. The SEM analysis then rejected H2b, due to the non-significant finding for AI gender. This hypothesis stream rejected four of five hypotheses, which suggests that further research is required to create a true understanding of participants' cognitive responses. Therefore, future research regarding how the usefulness of the AI website can be improved is needed. These findings can potentially be discovered through a number of methods; however, future researchers are recommended to seek an understanding of what AI development is required to improve users' cognitive responses. This will create an understanding of how AI can be developed to be perceived as useful and easy to use, while also functioning as intended, to increase users' cognitive responses based on their experience with AI. To create this understanding, participants may require a real life AI to be subjected to.

5.2.1.3 Hypothesis Three: Summary

The final hypothesis stream of this research sought to understand the effects of participants' cognitive responses on their behavioural responses. The three-way ANCOVA discovered that four of the five cognitive responses were significant, with only website credibility found to be non-significant at predicting usage and purchase intention. These findings were expected, based on discoveries within previous studies. Website believability had been discovered to influence users' immersion in a website (Zha et al., 2018), attitudes to environmental stimuli

(Lewis, 2009), and increase their behavioural responses (Janssen et al., 2016). Positive website sense of presence has been found to increase users' buyer goals (Hunter & Mukerji, 2011), increase consumers' browsing and shopping time (Eroglu et al., 2001), and influence users' behavioural responses (Fortin & Dholakia, 2005; Hunter & Mukerji, 2011; Yoon et al., 2015). Website involvement has been discovered to increase users' behavioural responses (Hepola et al., 2020; Hidayatullah et al., 2020; Kim et al., 2020). Lastly, technology helpfulness has been discovered to increase users' behavioural response (Chiu et al., 2005; Filieri et al., 2018; Lee et al., 2017; Liao et al., 2020; Waytz et al., 2014). The SEM further confirmed H3a, H3b, H3c, and H3e, however rejected H3d due to the non-significant relationship found between website involvement and its ability to predict usage intention. Overall, this hypothesis steam will further the knowledge and understanding available for future research and AI developers to create a more adoptable and well-rounded technology.

5.2.2 *Hypothesis One: Purchase Type, Artificial Intelligence Gender, and Anthropomorphism Level, will have a Direct Effect on Participants' Behavioural Responses*

Hypothesis One examined the role of purchase type, AI gender, and anthropomorphism level on participants' (H1a) usage intentions and (H1b) purchase intentions. This hypothesis stream was conceptualised in anticipation that the manipulation of the three independent variables would create an understanding of how users' behavioural responses to the AI website could be enhanced to assist future AI developers, by providing a theoretical background for creating adoptable AI software. This prediction was based on multiple studies that found AI gender, purchase type, and anthropomorphism level, positively affected users' usage and purchase intentions (behavioural responses).

Previous studies alluded to the influence of AI gender's effect on consumers' behavioural responses, due to various factors such as gender stereotypes (Tay et al., 2014), users' gender (Hanus & Fox, 2015; Morante et al., 2017; Nowak & Rauh, 2005), and gender bias (Wellner, 2020). A consumer's purchase type had previously been found to influence their behavioural responses to technology. For example, past studies found that aspects such as hedonic purchase and attitude (Peng & Kim, 2014; Suparno, 2020), hedonic purchase and positive user emotions (Chaudhuri et al., 2010; Zheng et al., 2019), product visual appeal (Zheng et al., 2019), and hedonic involvement (Chaudhuri et al., 2010), were all found to significantly increase consumers' behavioural responses. Finally, previous literature has identified that high levels of anthropomorphism have a direct influence on consumers' behavioural responses (Han, 2021; Jia et al., 2021; Laksmidewi et al., 2017). However, anthropomorphism was shown to require various features for it to influence consumers' behavioural responses (Laksmidewi et al., 2017). Therefore, positively manipulating AI gender and purchase types with anthropomorphism level to directly influence consumers' behavioural response was a major purpose of this research.

The following sections highlight the specific findings of H1 in relation to previous literature.

5.2.2.1 Discussion of H1a Findings: Usage Intention

The results of the three-way ANCOVA identified that the three independent variables did interact positively to directly influence participants' usage intention (behavioural response). This finding was expected based on the literature used to inform this hypothesis (see Laksmidewi et al., 2017), where the manipulation of multiple variables along with anthropomorphism level influenced users' behavioural response. However, individually, AI gender, purchase type, and anthropomorphism level had no major effect on usage intention, contradicting the majority of the previous literature (Han, 2021; Jia et al., 2021; Peng & Kim, 2014; Suparno, 2020; Tay et al., 2014). The SEM further confirmed this finding, which was expected, as all three independent variables were identified as significant ($p < 0.05$) at explaining the variance observed with participants usage intention. Furthermore, one finding of this hypothesis was the influence of users' overall mood'. A medium effect size was discovered, confirming the findings of previous studies (Schmid & Mast, 2010), with a user's positive mood prior to being subjected to an environmental stimulus, influencing their behavioural response positively.

5.2.2.2 Discussion of H1b Findings: Purchase Intention

The results of the three-way ANCOVA identified that the three independent variables did not interact positively, with no direct influence being found for participants' purchase intention (behavioural response). Individually, AI gender, purchase type, and anthropomorphism level, did not have any direct effects on participants' behavioural response, contradicting the findings of previous literature (Han, 2021; Jia et al., 2021; Peng & Kim, 2014; Suparno, 2020; Tay et al., 2014). However, the SEM analysis overturned this finding, as all three independent variables were identified as being significant ($p < 0.05$), therefore H1b was supported. This was expected based on the findings of previous studies (Han, 2021; Jia et al., 2021; Peng & Kim, 2014; Suparno, 2020; Tay et al., 2014), as the interaction of all three independent variables did positively influence a participants behavioural response. Building on H1a's finding, a users' overall mood' was confirmed as having an effect on their behavioural response, further confirming previous literature (Schmid & Mast, 2010).

5.2.3 Hypothesis Two: Purchase Type, Artificial Intelligence Gender, and Anthropomorphism Level, will have an Effect on Participants' Cognitive Responses

The second hypothesis stream examined the role of purchase type, AI gender, and anthropomorphism level, on participants' cognitive responses (H2a: website credibility; H2b: website believability; H2c: website sense of presence; H2d: website involvement; and H2e: technology helpfulness) with Ryan's Travel's AI website. This hypothesis was conceptualised in anticipation that the manipulation of the three independent variables would create an understanding of how users' cognitive responses to the AI website could be enhanced to assist future AI developers, by providing a theoretical background to creating adoptable AI travel itinerary software. This prediction arose from the findings of previous literature, with purchase type, AI gender, and anthropomorphism level all, both individually and collectively, being found to affect consumers' cognitive responses (i.e., website credibility, website believability, website sense of presence, website involvement and technology helpfulness).

Artificial intelligence gender and the gender of the user was found to significantly affect a user's views of: website credibility and believability (Craciun & Moore, 2019); sense of presence (Yoon et al., 2015); website involvement (Hanus & Fox, 2017; Morante et al., 2017); and technology helpfulness (Lehdonvirta et al., 2011; Lehdonvirta et al., 2012). Purchase type had previously been determined to effect consumers cognitive responses, including: website credibility and believability (Suparno, 2020); website sense of presence (Yoon et al., 2015); website involvement (Hollebeek, 2011; Hollebeek et al., 2014; Sarkar & Sarkar, 2019); and technology helpfulness (Moore, 2015; Sun & Spears, 2012). Finally, anthropomorphism level was discovered to significantly effect users cognitive responses, including: website credibility and believability (Alves & Soares, 2017; Nowak, 2000); website sense of presence (Nowak & Biocca, 2003); website involvement (Aggarwal &

McGill, 2007; Sivaramakrishnan et al., 2007); and technology helpfulness (Kääriä, 2017; Waytz et al., 2014).

The following sections highlight the specific findings of H2 in relation to previous literature.

5.2.3.1 Discussion of H2a Findings: Website Credibility

The results of the three-way ANCOVA identified that the three independent variables did interact positively, indicating the significant influence of participants' website credibility responses. This finding confirms those in prior research on the significant influence of AI gender (Craciun & Moore, 2019), hedonic purchase type (Suparno, 2020) and high anthropomorphism level (Alves & Soares, 2017; Nowak, 2000), on users' perceptions of the credibility of a website. Although the literature identified each independent variable as having an influence, only AI gender was shown to significantly affect website credibility, confirming the findings of Craciun and Moore (2019). The SEM further confirmed this finding, as all three independent variables were identified as being significant ($p < 0.05$) to explain the variance observed within participants website credibility response. Furthermore, the influence of users' overall mood was found to have a medium effect on their cognitive response of website credibility. This finding confirms those of Schmid and Mast (2010), as users' positive moods prior to being subjected to the environmental stimuli were found to influence their perceptions of the credibility of the website.

5.2.3.2 Discussion of H2b Findings: Website Believability

The results of the three-way ANCOVA identified that the three independent variables did interact positively, indicating the significant influence of participants' website believability responses, supporting this hypothesis. This finding confirms those in prior research on the influence of AI gender (Craciun & Moore, 2019), hedonic purchase type (Suparno, 2020) and high anthropomorphism (Alves & Soares, 2017; Nowak, 2000), on users' perceptions of website believability. Although all previous studies on this topic identified an individual effect, no individual effects were found to influence website believability in the current research. Although the three-way ANCOVA analysis discovered a positive interaction between website believability and the independent variables, the SEM discovered that AI gender was non-significant at influencing participants website believability ($p > 0.05$). Therefore H2b was overturned and not-supported. One interesting finding was the impact of users' overall moods on website believability responses. A large effect size was found, further confirming Schmid and Mast's (2010) finding, as a user's mood prior to being subjected to a stimulus impacted on how they perceived and responded to the environmental stimuli.

5.2.3.3 Discussion of H2c Findings: Website Sense of Presence

The results of the three-way ANCOVA identified that the three independent variables did not interact positively, with no influence being found for participants' responses to website sense of presence, based on the manipulation of AI gender, purchase type and anthropomorphism level. Individually, none of the three independent variables were found to have any effect on participants' website sense of presence response. This contradicted the findings of previous literature that identified hedonic purchases and AI gender (Yoon et al., 2015), and high anthropomorphism (Nowak, 2001; Nowak & Biocca, 2003) as having an effect on users' website sense of presence response. The SEM confirmed this finding, as AI gender was found to be non-significant ($p > 0.05$). The only findings from this hypothesis, was the impact of users' overall mood prior to the experiment. A large effect size was discovered, further confirming the prediction of Schmid and Mast (2010).

5.2.3.4 Discussion of H2d Findings: Website Involvement

The results of the three-way ANCOVA analysis revealed that the three independent variables both individually and in the interaction of the three, did not influence consumer involvement with AI. This finding was contradictory to the findings of previous research, which suggested that website involvement was influenced by hedonic purchases (Hollebeek, 2011; Hollebeek et al., 2014; Sarkar & Sarkar, 2019), AI gender (Hanus & Fox, 2015; Morante et al., 2017), and high anthropomorphism (Aggarwal & McGill, 2007; Sivaramakrishnan et al., 2007). The SEM confirmed this finding, as AI gender was found to be non-significant ($p > 0.05$). However, one interesting finding was that of the impact of consumers' overall mood prior to being subjected to an environmental stimulus. A medium effect size was found, as users' overall mood was found to influence their response to website involvement.

5.2.3.5 Discussion of H2e Findings: Technology Helpfulness

The results of the three-way ANCOVA analysis revealed that the three independent variables both individually and in the interaction of the three, did not influence participants helpfulness response. Although previous studies discussed various impacts, such as those of hedonic purchase's (Moore, 2015; Sun & Spears, 2012), AI genders' influence (Lehdonvirta et al., 2011; Lehdonvirta et al., 2012), and high anthropomorphism (Kääriä, 2017; Waytz et al., 2014), this study found no significant relationships impacting users' response to technology helpfulness. The SEM confirmed this finding, as AI gender was found to be non-significant ($p > 0.05$). The only findings from this hypothesis, was the impact of users' overall mood prior to the experiment. A medium effect size was discovered, further confirming the prediction of Schmid and Mast (2010).

5.2.4 Hypothesis Three: Cognitive Response will have a Significant Effect on Participants' Behavioural Response

The third and final hypothesis stream examined how each of the five cognitive responses (H3a: website credibility; H3b: website believability; H3c: website sense of presence; H3d: website involvement; and H3e: technology helpfulness) could be used to predict participants' behavioural responses (usage and purchase intention). This hypothesis was conceptualised in anticipation that the higher a participant's cognitive response, the higher their behavioural response; this was predicted due to the findings in the literature, as discussed next.

Website credibility and believability were previously found to influence users attitude towards a study (Lewis, 2009), as positive responses were found to influence users' behavioural response positively (Janssen et al., 2016; Zha et al., 2018). Hunter and Mukerji (2011) explained that a user's positive website sense of presence, significantly influenced their behavioural responses, with the inverse being found from a negative response. Several studies identified that consumers' successful website involvement response influenced their intention to purchase (behavioural response) within an online setting (Hepola et al., 2020; Hidayatullah et al., 2020; Kim et al., 2020). Lastly, technology helpfulness was found to be a key component of a successful and adoptable website (Filieri et al., 2018; Ghosh, 2018; Liao et al., 2017), with the helpfulness of a technology being found to increase consumers' purchasing behaviour regardless of how they rated their experience with a website (Lee et al., 2017). Due to these findings, this study predicted that users response to the five cognitive variables could be used to predict their behavioural responses.

The following sections highlight the specific findings of H3 in relation to previous literature.

5.2.4.1 *Discussion of H3a Findings: Website Credibility*

Two simple linear regression analyses were conducted to understand if participants' usage and purchase (behavioural response) intentions could be predicted by their perceptions of website credibility. These analyses rejected this hypothesis, as website credibility was found to be non-significant at predicting participants usage and purchase intentions via AI. This finding was unexpected, based on the findings of previous research. Positive website credibility has been found to influence participant immersion (Zha et al., 2018), attitudes towards environmental stimuli (Lewis, 2009) and increased behavioural response (Janssen et al., 2016). Furthermore, the credibility of a website and technology was shown to have positive effects on information usefulness, which further impacts users' behavioural response towards technology (Sussman & Siegal, 2003). Although previous literature had previously found a significance, the SEM's findings agreed with the initial linear regression analyses. The SEM found that website credibility was found to be non-significant ($p > 0.05$) at predicting both usage and purchase intention, therefore H3a was not supported.

5.2.4.2 *Discussion of H3b Findings: Website Believability*

Two simple linear regression analyses were conducted to understand if participants' usage and purchase (behavioural responses) intentions could be predicted by their perceptions of website believability. Both analyses confirmed there was a significance between participants' website believability response and their behavioural responses. This finding was expected, based on the findings of previous studies. Positive website believability had been found to influence participant immersion (Zha et al., 2018), attitudes towards environmental stimuli (Lewis, 2009), and increase behavioural responses (Janssen et al., 2016). The SEM confirmed this finding, with website believability significantly ($p < 0.05$) predicting both usage and purchase intention.

5.2.4.3 *Discussion of H3c Findings: Website Sense of Presence*

Two simple linear regression analyses were conducted to understand if participants' usage and purchase (behavioural responses) intentions could be predicted by their perceptions of website sense of presence. Both analyses confirmed there was a significance between participants' website sense of presence response and their behavioural responses. These findings were expected, based on the findings of previous studies. Positive website sense of presence has been found to increase users' buying goals (Hunter & Mukerji, 2011), and consumers' browsing and shopping time (Eroglu et al., 2001; Hunter & Mukerji, 2011), while increasing users' behavioural responses (Fortin & Dholakia, 2005; Hunter & Mukerji, 2011; Yoon et al., 2015). The SEM confirmed this finding, with website sense of presence significantly ($p < 0.05$) predicting both usage and purchase intention.

5.2.4.4 Discussion of H3d Findings: Website Involvement

Two simple linear regression analyses were conducted to understand if participants' usage and purchase intentions (behavioural responses) could be predicted by their perception of website involvement. Both analyses confirmed there was a significance between participants' website involvement response and their behavioural responses. These results were expected, based on the findings of previous studies. Behavioural responses were previously found to be influenced by users' website involvement (Hepola et al., 2020; Hidayatullah et al., 2020; Kim et al., 2020). Corresponding aspects have also been found to have an effect alongside website involvement on users' behavioural responses, such as the perceived flow of the website (Hidayatullah et al., 2020), and attachment to the experience (Kim et al., 2020). However, the SEM found the inverse, as website involvement was found to be non-significant ($p > 0.05$) at predicting usage intention, therefore H3d was not supported.

5.2.4.5 Discussion of H3e Findings: Technology Helpfulness

Two simple linear regression analyses were conducted to understand if participants' usage and purchase (behavioural responses) intentions could be predicted by their perception of technology helpfulness. Both analyses confirmed there was a significance between participants' technology helpfulness response and their behavioural responses. These results were expected, based on the findings of previous studies explained that the helpfulness of technology had an influence on users' behavioural responses (Chiu et al., 2005; Filieri et al., 2018; Lee et al., 2017; Liao et al., 2020; Waytz et al., 2014). Furthermore, reduced frustration was found to increase technology helpfulness (Filieri et al., 2018), technology helpfulness was discovered to influence consumers' purchasing behavioural regardless of how they rated their experience (Lee et al., 2017), and high levels of anthropomorphism were discovered to influence the perceived helpfulness of the technology (Waytz et al., 2014). The SEM confirmed this finding, with technology helpfulness significantly ($p < 0.05$) predicting both usage and purchase intention.

5.3 Discussion of Key Findings

The results of this research identified multiple significant interaction effects between the manipulation of purchase type, AI gender, and anthropomorphism level, and the influences on participants' purchase intention, usage intention, and website credibility. Furthermore, this research discovered that participants' response to three cognitive responses (website believability, website sense of presence, and technology helpfulness) could predict their behavioural responses towards operating and purchasing using AI travel itinerary software. The research also discovered the control variable ("users' overall mood") influenced participants' response to the environmental stimuli and the overall influence of all five cognitive responses and both behavioural responses (usage intention, and purchase intention via AI). The key direct effect discovered by this research was the influence of the environmental stimuli that participants were subjected to, on their behavioural response. It was discovered that the manipulation of the three independent variables ("AI gender," "purchase type," and "anthropomorphism level") had a significant influence on users' behavioural responses (usage and purchase intention via AI). The three way ANCOVA analysis identified that individually, each independent variable was found to have no significant effect on participants' usage and purchase intention. However, this was expected, based on the findings of Laksmidewi et al. (2017), who explained that various features are required to influence consumers' usage intention, along with the influence of anthropomorphism. In saying this, the SEM found that users behavioural responses were significantly affected by all three independent variables individually, confirming the findings of previous studies (Chaudhuri et al., 2010; Han, 2021; Jia et al., 2021; Laksmidewi et al., 2017; Tay et al., 2014).

Prior research explained that artificial intelligence gender was expected to influence users' intention to use AI technology. Tay et al. (2014) explained the need for future research into AI gender stereotypes, as AI users were found to be comfortable when the job the AI was fulfilling aligned with current job stereotypes. Furthermore, the gender of a user was found to increase their usage intention when the gender aligned with that of the user (Morante et al., 2017; Nowak & Rauh, 2005). However, male AI had been reported as more masculine and less attractive than were female avatars, these factors have been found to influence users' behavioural responses towards a technology (Nowak & Rauh, 2005). Purchase type had been extensively researched in previous studies, to understand its impact on consumers' behavioural responses. Hedonic purchases were all found to positively influence consumers' behavioural responses compared to those of utilitarian purchases (Chaudhuri et al., 2010; Peng & Kim, 2014; Suparno, 2020; Zheng et al., 2019). Lastly, high levels of anthropomorphism had been found to positively and directly influence consumers' behavioural responses (Han, 2021; Jia et al., 2021; Laksmidewi et al., 2017). This direct effect occurred because human-like technology was found to be held more accountable than was robotic technology, which positively influenced the interaction between the user and the technology (Waytz et al., 2014; Złotowski et al., 2015).

The context of this research was the use of a personalised travel itinerary AI website, developed to provide consumers with a quick, easy, and technologically advanced travel itinerary service, with the capacity to revolutionise travel itinerary planning. The influence of AI gender stereotypes (Tay et al., 2014; Wellner, 2020), purchase types (Peng & Kim, 2014; Suparno, 2020; Zheng et al., 2019), and anthropomorphism levels (Han, 2021; Jia et al., 2021; Laksmidewi et al., 2017) when designing this AI system was of extreme relevance, as potential users required an easily adoptable AI that efficiently demonstrated its usefulness and usability features. This research intended to find a significant positive relationship between the environmental stimuli and participants' behavioural responses. However, no significant relationship was discovered for the manipulation of environmental stimuli on users' purchase intention. Although a large body of previous research explained that there was an effect, no previous research incorporated and manipulated all three independent variables to understand their collective effect. The lack of significance found from the three-way ANCOVA analysis in H1b's findings may have occurred for numerous reasons, including but not limited to the limitations of the scenario, poor manipulation of independent variables (anthropomorphism level), use of a video to demonstrate the AI, or COVID-19's impact on consumers' likelihood to purchase a travel itinerary during such an uncertain time (e.g., in terms of financial and cancellation risks etc). However, the SEM analysis contradicted and overturned this finding, as purchase intention was found to be influenced by AI gender, purchase type, and anthropomorphism level. The SEM analysis compared the influence of all variables at the same time, rather than individually, this discovered that purchase intention was significantly impacted by each of the three independent variables, supporting H1b. Therefore, the findings of the first hypothesis stream confirmed the findings of previous literature (Chaudhuri et al., 2010; Han, 2021; Jia et al., 2021; Laksmidewi et al., 2017; Tay et al., 2014; Waytz et al., 2014), that identified AI gender, purchase type, and anthropomorphism level having a significant effect on consumers purchase and usage intentions.

Two interesting effects were discovered from this research's three-way ANCOVA analyses; these were in the impacts of the environmental stimuli on two cognitive responses (website credibility and website believability). Previous studies had determined that both website credibility and believability influenced the immersion experience of a user (Zha et al., 2018), and the attitudes formed towards a study's environmental stimuli (Lewis, 2009). Both cognitive responses deal with how an experience is portrayed by a user's AI gender (Craciun & Moore, 2019), purchase type (Suparno, 2020) and anthropomorphism level (Nowak, 2000), all of which had been previously discovered to influence a user's perception of website credibility and believability. However, contradictory to the three-way ANCOVA analysis the SEM found that website believability was not supported, although individually believability was influenced, when analysed with multiple other variables, participants responses were unaffected. Therefore, H2b was rejected.

The second hypothesis stream sought to understand the effect of all five cognitive responses (website credibility, website believability, website sense of presence, website involvement, and technology helpfulness) on the manipulation of environmental stimuli. Although, prior research had found relevance, website believability, website sense of presence, website involvement, and technology helpfulness was not influenced by the studies environmental stimuli. This may have been due to the research method, as users require a hands-on experience to understand how involved, present, and helpful a technology is; a video cannot give participants the opportunity to actually use a website, but just to demonstrate its capabilities. Future research should attempt to create a usable AI software, to understand how the manipulation of AI gender, purchase type, and anthropomorphism level affects all five cognitive responses, to create an understanding for future AI developers to use as a guide for AI software development.

The third hypothesis stream discovered that users' cognitive responses could be used to determine their behavioural responses. Previous studies had discovered that the same five cognitive responses used in this research had been found to influence and affect users' behavioural responses. Website credibility and believability (Janssen et al., 2016; Zha et al.,

2018) had been discovered to influence users' perceptions of immersion and attitudes towards environmental stimuli. Website sense of presence had been discovered to influence users' buying goals and browsing time (Fortin & Dholakia, 2005; Hunter & Mukerji, 2011; Yoon et al., 2015), and website involvement had been found to influence users' response to a website (Hepola et al., 2020; Hidayatullah et al., 2020; Kim et al., 2020). Finally, technology helpfulness was identified to impact users' overall response and intention to use a website in a variety of contexts (Chiu et al., 2005; Filieri et al., 2018; Lee et al., 2017; Liao et al., 2020; Waytz et al., 2014).

Although the linear regression analysis confirmed four of the five hypotheses within the third hypothesis stream, the SEM found H3d to be non-significant. Website involvement was found to have no influence on usage intention via AI, while the SEM confirmed the three-way ANCOVA findings of H3a, as website credibility had no influence on usage and purchase intention via AI. The difference in findings is due to the purpose of the SEM, which is to identify which variables are significant when all variables are being interpreted by the participants at the same time. This SEM analysis discovered that H3a and H3d did not influence participants' usage and purchase intentions.

The supported finding of H3b, H3c, and H3e informs future AI developers and future research of the importance of an all-inclusive service; each cognitive response is concerned with creating a usable, useful, and easy to use service. Website believability is important to ensure users feel safe and are not using an unreliable website; creating a believable website is often the first important aspect of a user's experience (i.e., first impressions matter). As discovered by this study, a positive website believability was found to increase a user's behavioural responses, which is the ultimate outcome for AI developers. Website sense of presence ensures users are actively engaged with an AI technology. Ensuring a user is present while using the AI was found to be essential to increasing users behavioural response. As if a user isn't paying attention to the AI, long term adoption is unlikely to occur, due to the forgeability of their experience. Future AI developers and AI literature can utilise these findings by ensuring users are actively present at all times when using the AI software. Lastly, the helpfulness of the AI technology depends on how accurate the output of the AI is. An AI could provide the best service available to consumers, however, if the itinerary created by the AI is not personalised, is impossible to edit, or adds activities of no interest to the user, the technology will be destined to fail. Regardless of how credible and believable the technology is, or how present and involved the technology makes users feel, if the technology fails to deliver a personalised itinerary, usage and purchase intention will not be achieved.

The final finding of this research lies in the impact of users' overall mood prior to beginning the experiment. Schmid and Mast (2010) theorised that both positive and negative moods can have a wide variety of effects on consumers' decision making. Negative moods often result in consumers' negative attitudes to the stimuli they are exposed to, whereas positive moods cause consumers to think positively about the stimuli. This study discovered that users' overall mood before being subjected to the environmental stimuli, significantly influenced both behavioural responses and all five cognitive responses. This discovery explains that a user's overall mood prior to being subjected to the manipulation of AI gender, purchase type, and anthropomorphism level, impacted users' cognitive and behavioural responses. Users' negative moods resulted in a negative interpretation of the environmental stimuli, hindering their responses, whereas their positive moods facilitated positive responses. This discovery informs future research and AI developers of the importance of ensuring a user has a positive attitude before beginning their experience with AI technology.

5.4 Research Implications and Contributions

5.4.1 Theoretical Implications and Contributions

The findings identified within this thesis created various theoretical implications and contributions. The understanding of the direct effect that environmental stimuli have on participants' usage and purchase intention contributes to AI marketing knowledge, in that the environmental stimuli that users are subjected to must serve a purpose to influence users' behavioural response. What this refers to is when creating and conducting AI research, the stimuli must be relevant to the context of the technology. Travel itinerary planning is often a very hedonic and emotional experience, and will require human-like properties to directly influence users' behavioural response (Suparno, 2020). It is also a very trusting experience; often travellers will have their own travel agent, someone who understands the wants and needs of their client, therefore AI must create and adapt trusting attributes. This has been previously touched on by Jia et al, (2021), who explained that high levels of anthropomorphism are required to ensure a user trusts the technology as if it were a human (Jia et al., 2021). Tying in all of these points, an AI must be relevant to the industry or context it is trying to enter, as explained by Tay et al, (2014), who stated AI gender stereotypes require industry accurate representation to increase adoption. Future theoretical research must be heavily stringent when creating and designing AI, to ensure users behavioural responses are positively affected.

One key implication of this research is in the impact of the environmental stimuli on participants' purchase intentions, when analysed individually. Despite the findings of previous research, AI gender (Tay et al., 2014), purchase type (Suparno, 2020) and anthropomorphism level (Jia et al., 2021), had no significant direct effect on participants' purchase intentions. The three-way ANCOVA analysis within this study found that individually the three independent variables did not positively influence participants purchase intention. However, when analysing collectively with all other variables, the SEM discovered that purchase intention was influenced positively by each independent variable individually, as outlined and explained by previous literature. This explains that the purchase of an AI is all about the overall experience had by a user. By ensuring that the technology has high levels of anthropomorphism, successfully utilises its hedonic attributes, and has a life-like avatar will increase the likelihood of purchase, when compared to AI technologies that struggle to implement the same features.

A key contribution of this research is in the importance of an all-inclusive service to positively influence users' behavioural responses. Three cognitive responses (website believability, website sense of presence, and technology helpfulness) were identified as having a positive influence on participants' behavioural responses. This explains that all AI research should ensure a full service is presented to participants when researching AI software. Adoption of AI requires a highly useful and easy to use service to ensure no negative perceptions are created by the user.

The final contribution of this research is the confirmation of the impact a user's overall mood has on AI adoption. Schmid and Mast (2010) theorised that negative and positive moods influence participants' perceptions of environmental stimuli. This research builds upon their findings, to inform future research of the acceptability of BMIS within an AI experimental context.

5.4.2 *Managerial Implications*

This research's findings revealed four key managerial implications for future AI developers. The first was the understanding of the environmental stimulus's direct effect on participants' usage and purchase intention. The second was the effects discovered from the study's environmental stimuli on participants' cognitive response (website credibility). The third was the discovery three cognitive responses can be used to determine a user's behavioural responses, and lastly, was the understanding of users' overall mood prior to the experiment on their cognitive responses and purchase intentions.

Artificial intelligence developers, and AI service managers/companies can harness the understandings of AI gender, purchase type, and anthropomorphism level on users' behavioural responses. This study determined that participants' usage and purchase intentions towards Ryan's Travel AI were directly affected by the manipulation of the various aspects of the study's environmental stimuli. Building on the findings of previous literature, AI gender stereotypes (Tay et al., 2014), hedonic purchases (Suparno, 2020) and high levels of AI anthropomorphism (Jia et al., 2021), were all identified to increase and affect users' usage and purchase intentions. Artificial intelligence software developers, and AI service managers/companies can leverage this knowledge by creating AI with high usage and purchase intention characteristics. This may be accomplished by ensuring the gender of the AI follows the stereotype portrayed by the industry it is attempting to enter. This must be accomplished by first understanding what it is that the AI is intending to provide/sell, then matching the environmental stimuli characteristics to fit. For example, if an AI developer is intending to create a hedonic product or service website, then the AI must be created with hedonic characterises in mind. This will give users the understanding and trust that the product or service that is being offered is real and believable, just as a user would experience via a real human being.

A second managerial implication of this research that AI developers and AI companies will benefit from, is in understanding of the effect of the environmental stimuli manipulation on users' perceptions of website credibility. The correct manipulation of AI gender, purchase type, and anthropomorphism level, was found to increase users' perceptions of website credibility. Previous research had determined that ensuring a high level of anthropomorphism increases the accountability of a software (Waytz et al., 2014; Złotowski et al., 2015), which increases how credible the website is portrayed as. This study found that the purpose and context of an AI travel itinerary must be developed with no stereotypes, high levels of anthropomorphism, and utilise hedonic purchase intentions to increase users' perceptions of website credibility. Future AI developers and companies must design their AI with the correct environmental stimuli to match the product or service they are attempting to provide. This is important, as increasing users' perceptions of website credibility has been found to increase their immersion in a technology (Zha et al., 2018), which has been previously discovered to positively influence their behavioural responses.

A third managerial implication of this research is in the importance of an all-inclusive service to influence a positive behavioural response from the user. This research identified a positive effect for three of the five cognitive responses on users' behavioural responses. As previous studies alluded to, website believability (Janssen et al., 2016; Zha et al., 2018), website sense of presence (Fortin & Dholakia, 2005; Hunter & Mukerji, 2011; Yoon et al., 2015), and technology helpfulness (Chiu et al., 2005; Filieri et al., 2018; Lee et al., 2017; Liao et al., 2020; Waytz et al., 2014), all positively predict users' usage and purchase intentions. The three cognitive responses analysed within this research showed a substantial increase in participants' usage and purchase intentions. This research and the findings of previous research identified the overall importance of an all-inclusive experience for every user that engages with AI technology. Developers of AI must ensure that all functions of a website work as intended, to ensure that the service is both useful and usable for a user's purpose.

The final managerial implication is in the understanding of the effect of users' overall mood prior to using an AI. As predicted by Schmid and Mast (2010), both positive and negative moods were found to have an effect on consumers' decision making. Participants in pleasant moods were found to have increased usage and purchase intentions, compared with those who rated their moods as unpleasant. Due to the stereotype currently surrounding AI, any errors found within its service are meet with harsh criticism when compared to traditional services. This finding grants AI developers an understanding of the effect of mood, however, knowing how this understanding can be utilised to increase users' behavioural responses will be an important avenue for future research. Initially, developers of AI may consider using less ads on their sites, ensure sales are heavily presented and creating a nice and comforting AI experience while the technology is still in the early adopters stage of the technologies lifecycle. These users can then be subjected to a happier and less invasive service, with the intention to entice them to return when they are in a better mood, and ready to be subjected to the environmental stimuli, increasing their behavioural responses to the AI software.

5.5 Research Limitations

A key limitation of this research was the creation of Ryan's Travel, the AI created to give participants an understanding of how AI operates, by using labelled inputs (travel preferences) to create specific outputs (personalised itineraries). Ideally, the creation of AI would have given participants access to Ryan's Travel, allowing for the selection of participants' actual travel preferences, which would have created for each participant, their own personalised travel itinerary. However, the creation of such a technology was not feasible with the resources allocated for this study. Future research would benefit from giving participants access to real AI software, and assessing their opinions from their real experience.

Another limitation was in the use of videos in experimental design, as explained by Gong and Tung (2017). Although participants were instructed to imagine themselves purchasing a personalised holiday or business trip itinerary in the USA, it was not possible to determine if this was accurately interpreted by all participants. Future research should attempt to resolve this issue by providing participants with examples that do not require the interpretation of a scenario to collect data on their emotional feelings towards the AI software. This would allow for more accurate reasoning around users' true experience responses to AI.

A further potential limitation of this thesis may have been the difference created by separate levels of attractiveness in the avatars, the use of only one ethnicity (Caucasian) and the westernised names chosen for Jane and John. The USA has a diverse range of ethnicities, and this study was made up of 85.5% Caucasian, which is not a true reflection of the US population. Therefore, the use of unequal attractiveness between the two avatars, Caucasian avatars, and westernised names may have led to a limitation with the data.

The choice of a travel itinerary AI could also have hindered the data collected within this research, due to the restrictions on travel that COVID-19 presented in 2020. Participants contemplating the use of Ryan's Travel AI software could have given different responses to those in non-pandemic periods, as COVID-19 created a lasting impact on participants' willingness to travel during the unprecedented events of 2020. Future research should recreate this research method in five to ten years to understand if COVID-19 had an impact on the adoption of a travel itinerary AI, by comparing the results found in this research, against those of the later study.

5.6 Future Research

The purpose of this research was to build on the findings from previous studies, to extend knowledge on AI adoption and AI software development. In doing so, several future research streams were identified.

Firstly, aspects of anthropomorphism levels should be studied in further depth. The effects of ethnicity and perceived attractiveness should also be researched, to understand the effects on consumers, as this would provide AI developers the ability and knowledge to create a human-like AI that is perfect for the context for which it is designed. This research need was previously mentioned by Alves and Soares (2017) and Nowak and Rauh (2005), however, due to the resources and time available for this research, creating and understanding levels of ethnicity and attractiveness was not possible.

Secondly, and most importantly, future research is required with a real-life AI. Future research should be conducted utilising real AI software, so users can have a hands-on experience, giving users the ability to truly interpret the environmental stimuli they are subjected to. This would allow for extraordinary discoveries in terms of how users' cognitive and behavioural responses are influenced in a real-life setting. This would also provide an accurate understanding of how purchase type, AI gender, and anthropomorphism level, can be manipulated to increase and improve a user's experience with AI.

Lastly, future research should attempt to create an all-inclusive AI service. This would allow for an understanding of what is needed to increase AI's usefulness and usability aspects. Understanding how users' cognitive responses (website credibility, website believability, website sense of presence, website involvement, and technology helpfulness) can be created to be equally effective at influencing their behavioural responses (usage and purchase intention), would allow AI developers to create a more adoptable and usable service/technology.

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7 Appendix

Appendix A: Ethics Approval

UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND

HUMAN ETHICS COMMITTEE

Secretary, Rebecca Robinson
Telephone: +64 03 369 4588, Extn 94588
Email: human-ethics@canterbury.ac.nz

Ref: HEC 2020/21/LR

21 August 2020

Josh Ryan
UC Business School
UNIVERSITY OF CANTERBURY

Dear Josh

Thank you for submitting your low risk application to the Human Ethics Committee for the research proposal titled "Understanding Consumer Perceptions of AI".

I am pleased to advise that this application has been reviewed and approved.

Please note that this approval is subject to the incorporation of the amendments you have provided in your email of 17th August 2020.

With best wishes for your project.

Yours sincerely

Dr Dean Sutherland
Chair, Human Ethics Committee

Appendix B: Ryan's Travel - Video URL Links

Condition 1: https://youtu.be/yIOLKaWVbvo

Condition 2: https://youtu.be/sP2WJ0C4GY8

Condition 3: https://youtu.be/XfUwl3jscTc

Condition 4: https://youtu.be/DIDG4NUThUA

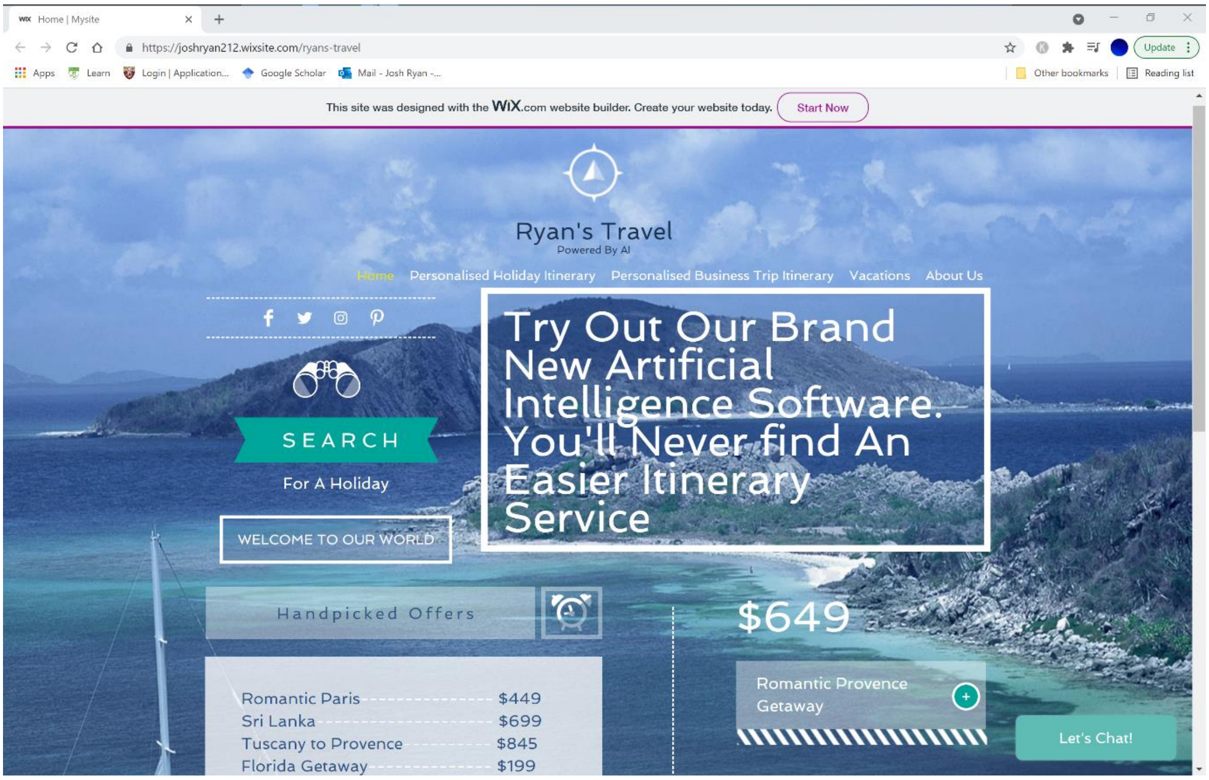
Condition 5: https://youtu.be/YLUXs7J9Jnk

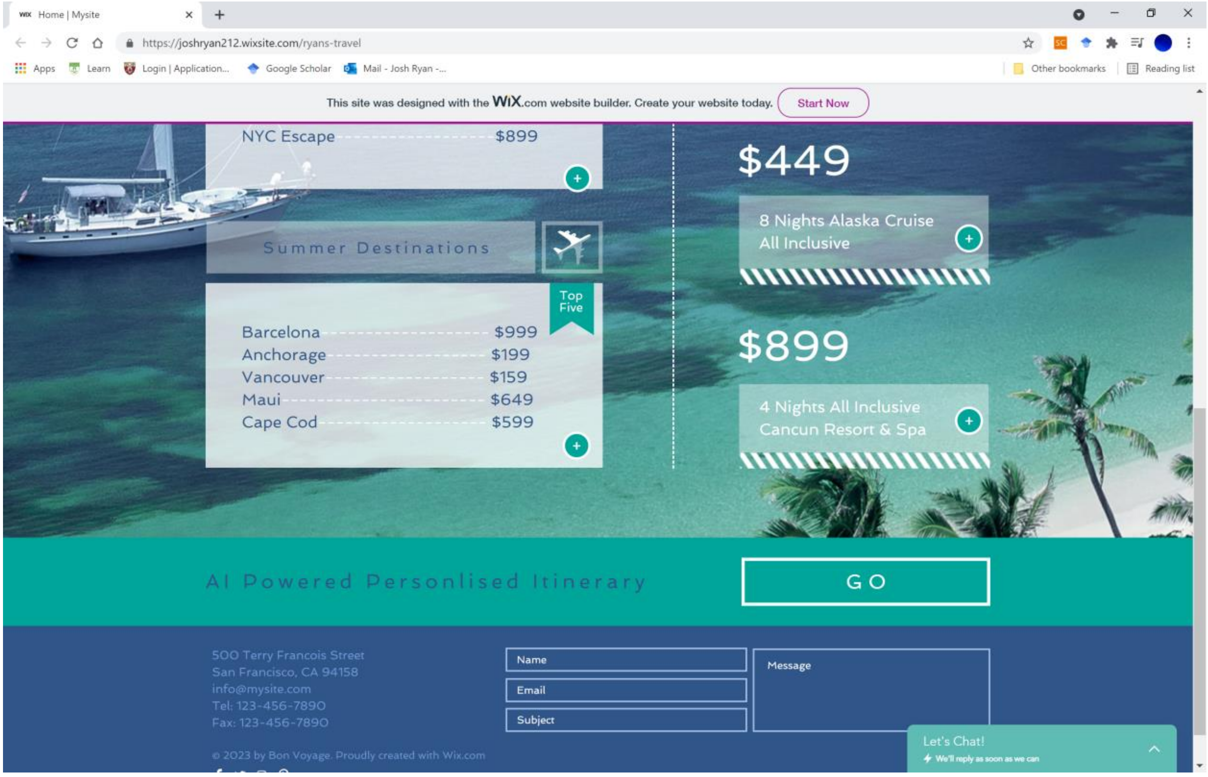
Condition 6: https://youtu.be/mYc5B9BfGwg

Condition 7: https://youtu.be/LtPYhdYJ8c0

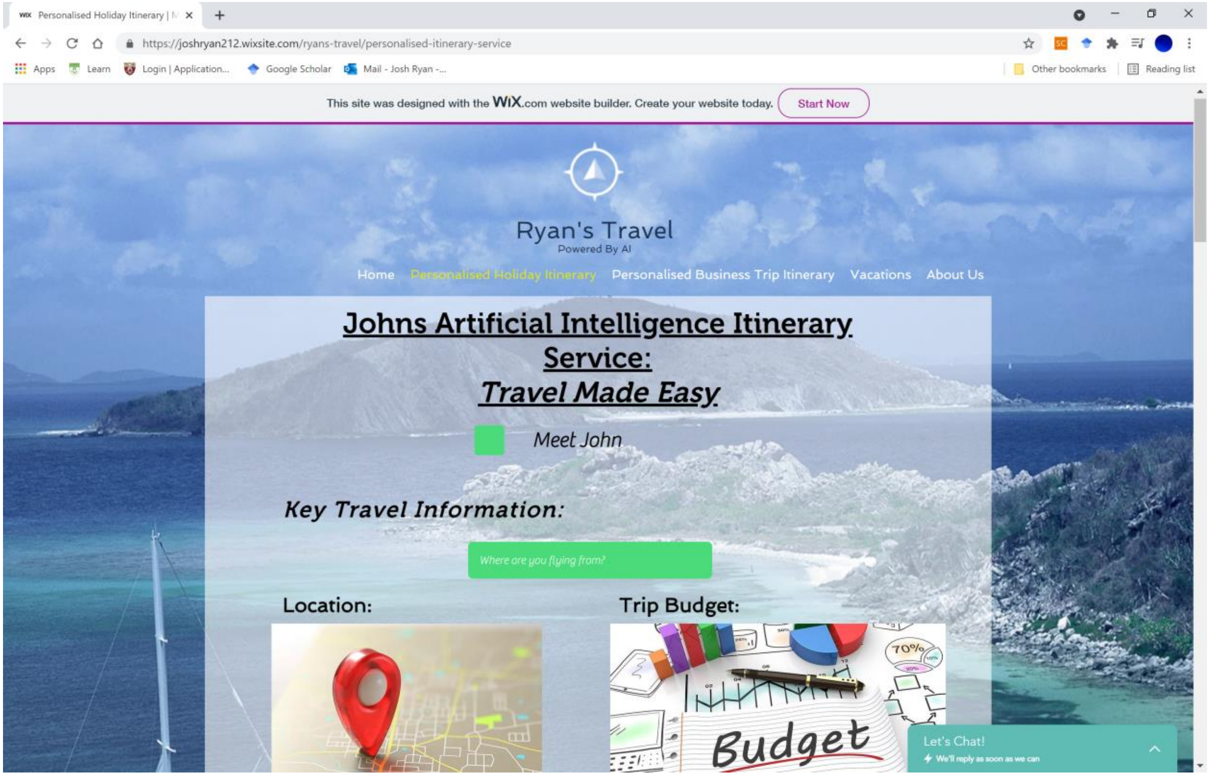
Condition 8: https://youtu.be/ttduygd1IZM

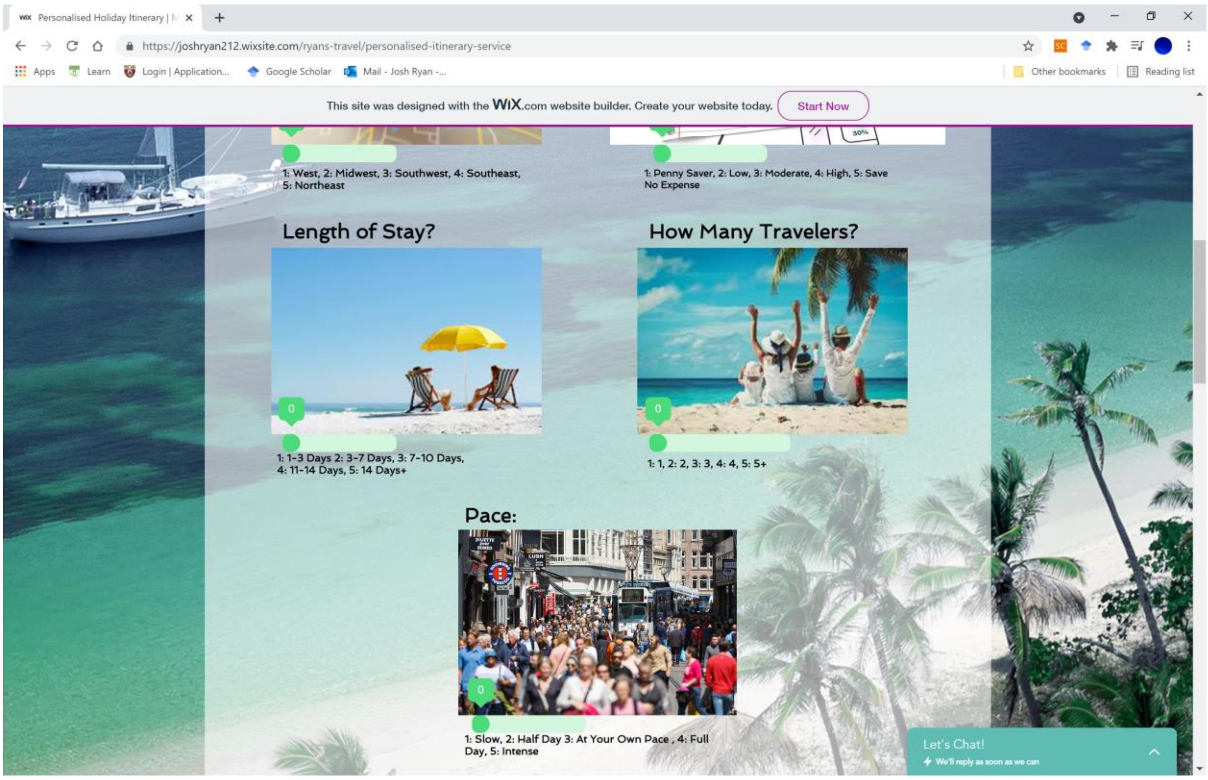
Appendix C: Ryan's Travel Website - Home Page

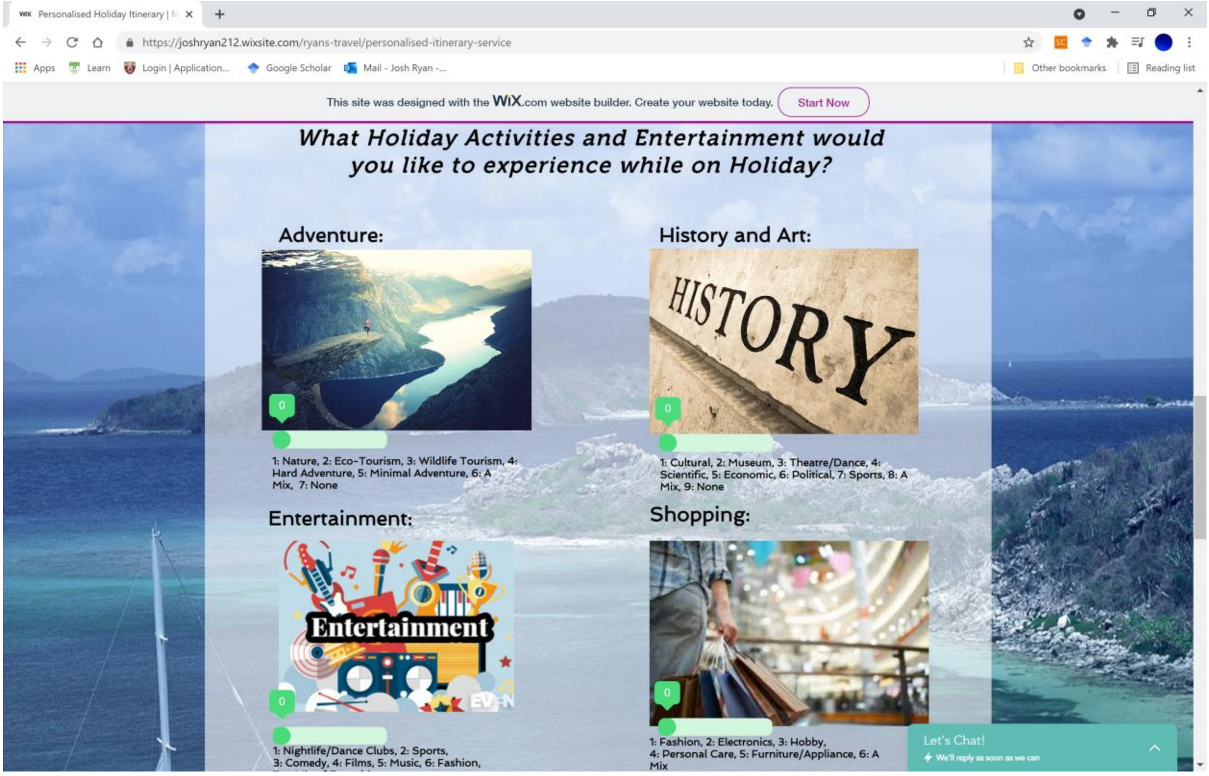


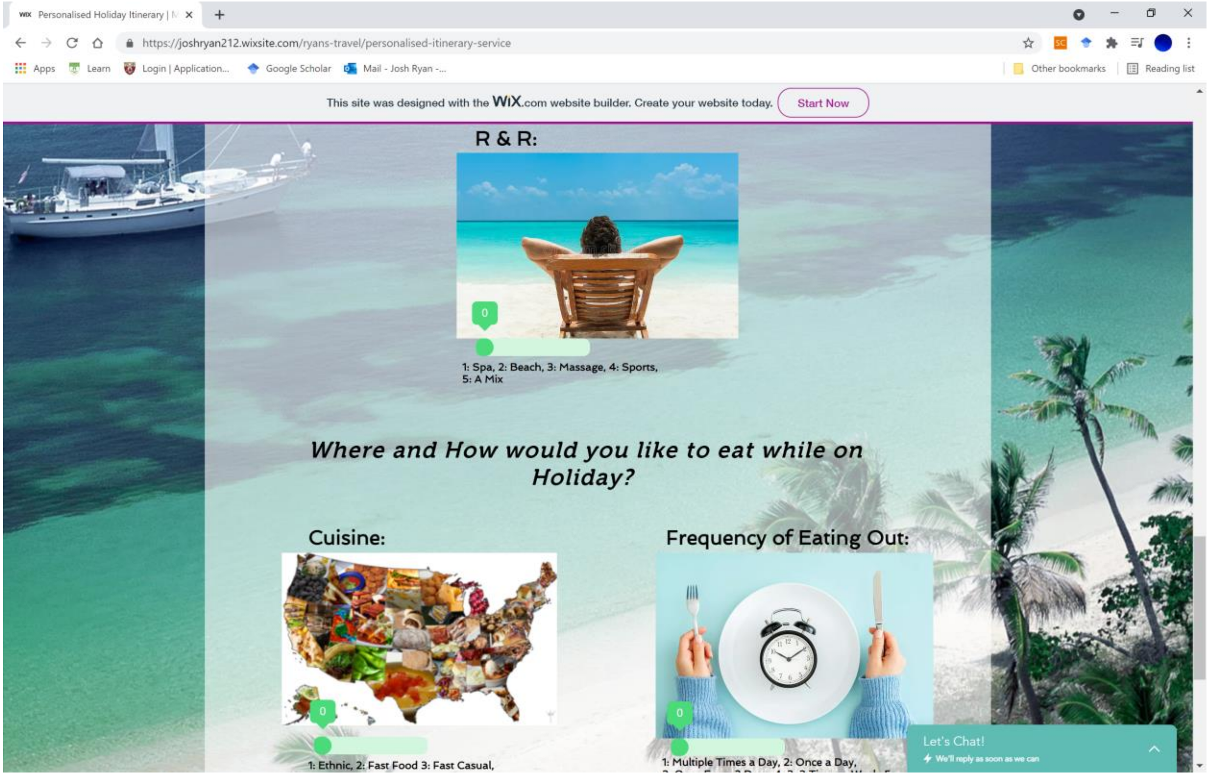


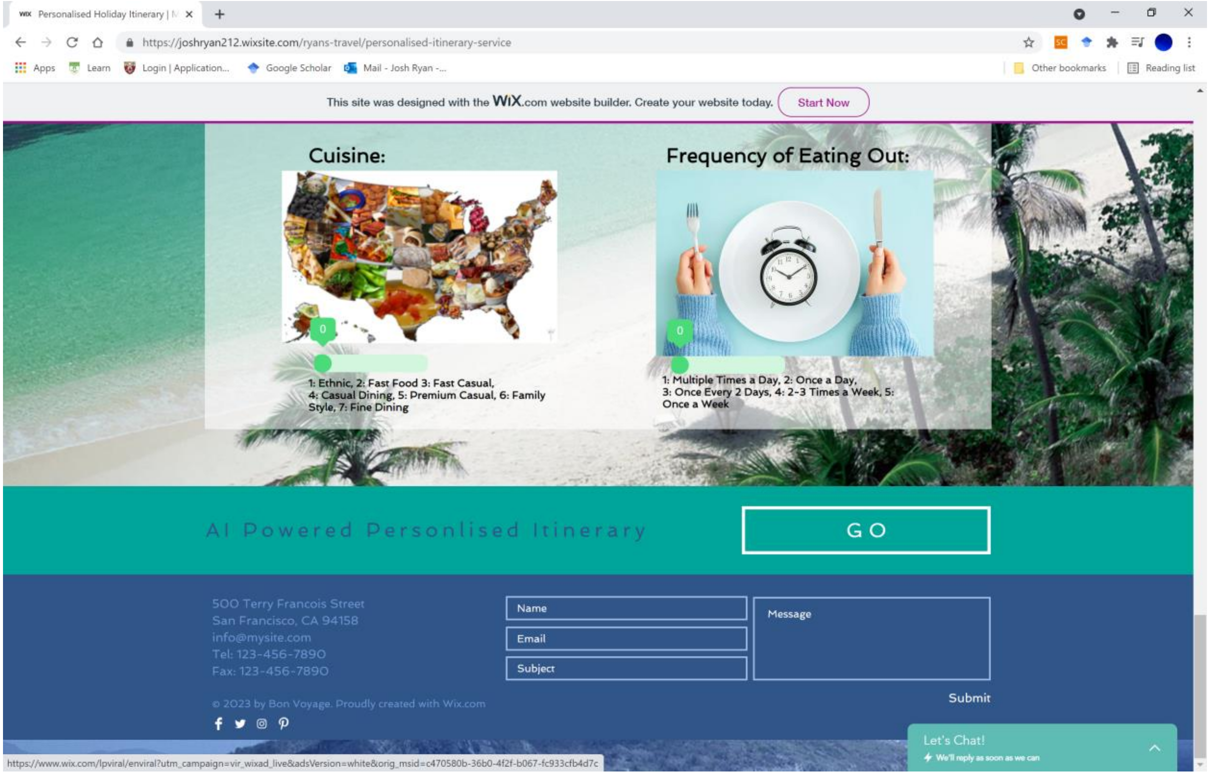
Appendix D: Ryan's Travel Website – Personalised Holiday Itinerary Page



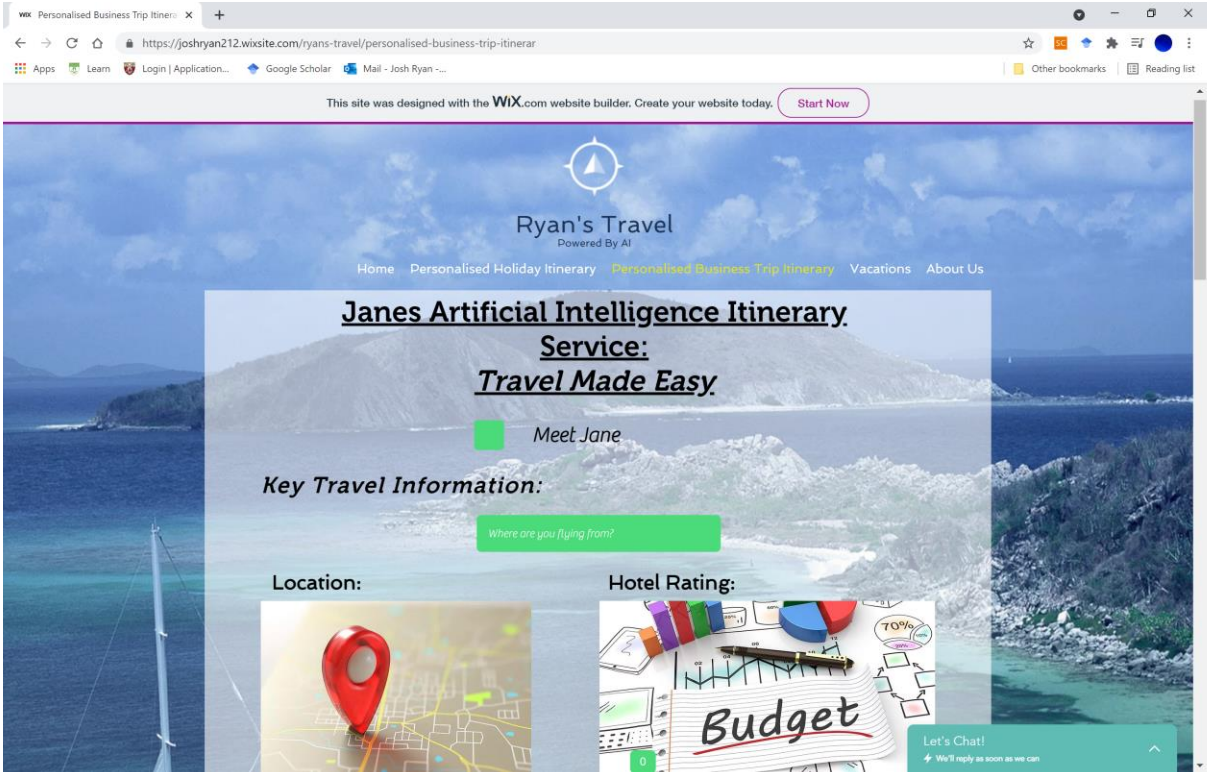


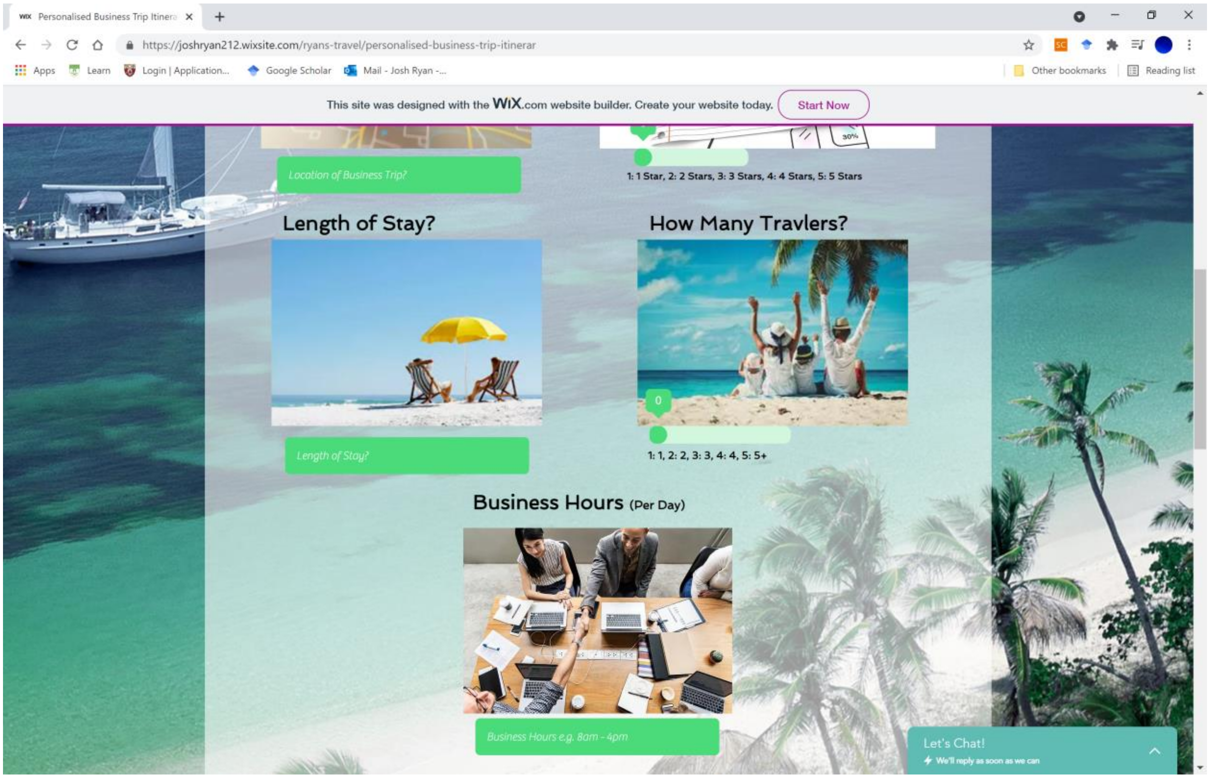

Personalised Holiday Itinerary
https://joshryan212.wixsite.com/ryans-travel/personalised-itinerary-service
This site was designed with the WIX.com website builder. Create your website today.
Start Now
What Holiday Activities and Entertainment would you like to experience while on Holiday?
Adventure:
History and Art:
HISTORY
1: Nature, 2: Eco-Tourism, 3: Wildlife Tourism, 4: Hard Adventure, 5: Minimal Adventure, 6: A Mix, 7: None
1: Cultural, 2: Museum, 3: Theatre/Dance, 4: Scientific, 5: Economic, 6: Political, 7: Sports, 8: A Mix, 9: None
Entertainment:
Shopping:
Entertainment
1: Nightlife/Dance Clubs, 2: Sports, 3: Comedy, 4: Films, 5: Music, 6: Fashion,
1: Fashion, 2: Electronics, 3: Hobby, 4: Personal Care, 5: Furniture/Appliance, 6: A Mix
Let's Chat!

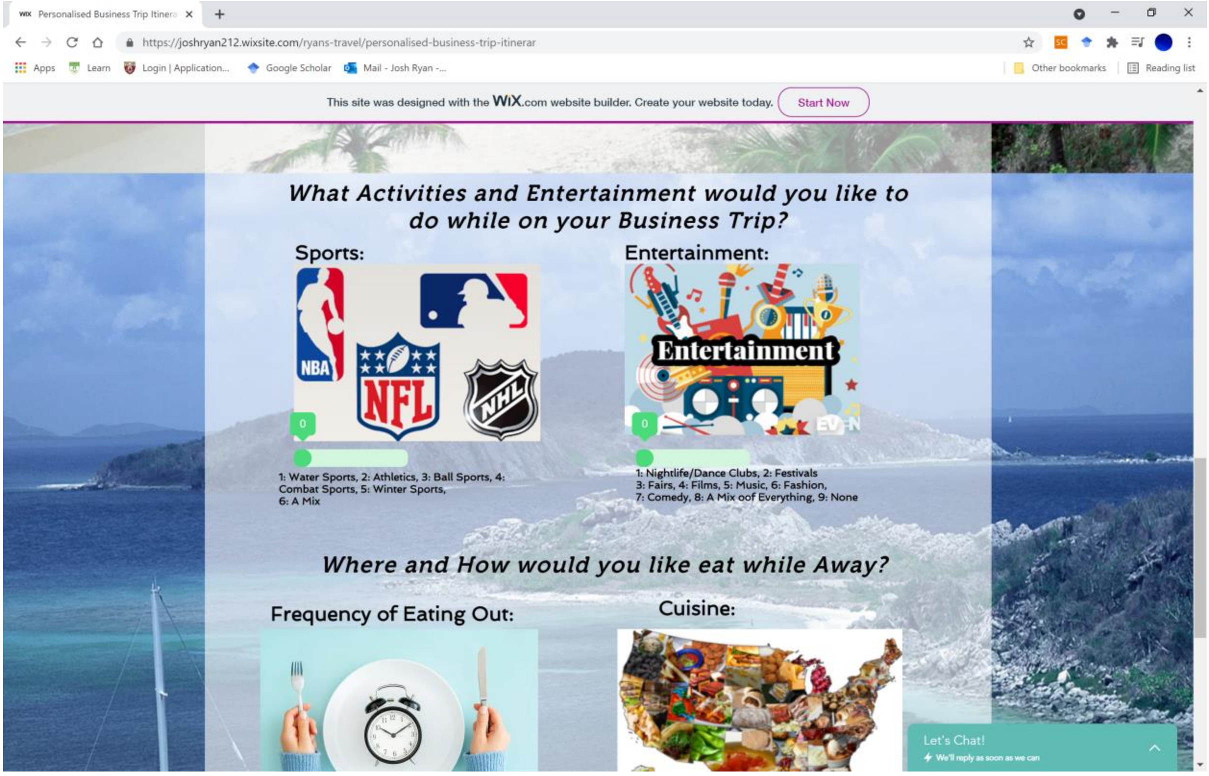

Personalised Holiday Itinerary
https://joshryan212.wixsite.com/ryans-travel/personalised-itinerary-service
This site was designed with the WIX.com website builder. Create your website today.
Start Now
R & R:
1: Spa, 2: Beach, 3: Massage, 4: Sports, 5: A Mix
Where and How would you like to eat while on Holiday?
Cuisine:
Frequency of Eating Out:
1: Ethnic, 2: Fast Food 3: Fast Casual,
1: Multiple Times a Day, 2: Once a Day,
Let's Chat!

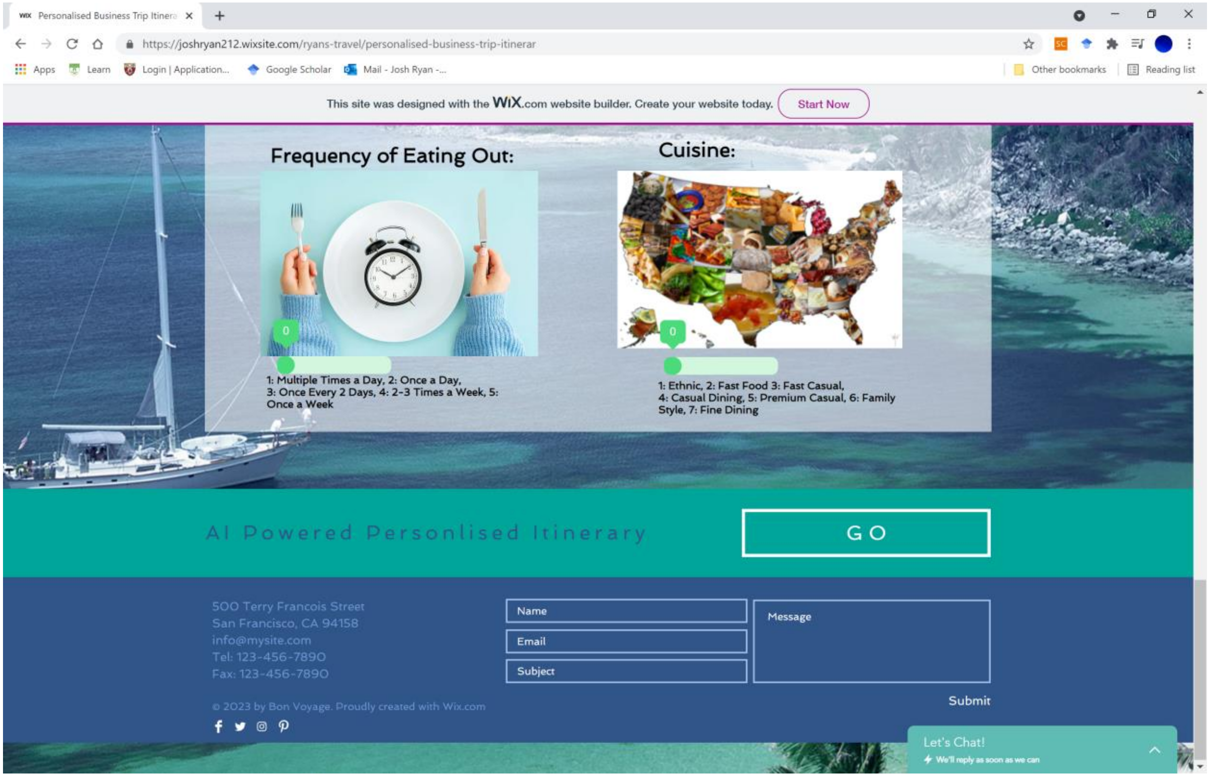

Personalised Holiday Itinerary
https://joshryan212.wixsite.com/ryans-travel/personalised-itinerary-service
Apps
Learn
Login | Application...
Google Scholar
Mail - Josh Ryan -...
Other bookmarks
Reading list
This site was designed with the WiX.com website builder. Create your website today.
Start Now
Cuisine:
0
1: Ethnic, 2: Fast Food 3: Fast Casual, 4: Casual Dining, 5: Premium Casual, 6: Family Style, 7: Fine Dining
Frequency of Eating Out:
0
1: Multiple Times a Day, 2: Once a Day, 3: Once Every 2 Days, 4: 2-3 Times a Week, 5: Once a Week
AI Powered Personlised Itinerary
GO
500 Terry Francois Street
San Francisco, CA 94158
info@mysite.com
Tel: 123-456-7890
Fax: 123-456-7890
© 2023 by Bon Voyage. Proudly created with Wix.com
Name
Email
Subject
Message
Submit
Let's Chat!
We'll reply as soon as we can
https://www.wix.com/lpviral/enviral?utm_campaign=vir_wixad_live&adsVersion=white&orig_msid=c470580b-36b0-4f2f-b067-fc933cfb4d7c

Appendix E: Ryan's Travel Website - Personalised Business Trip Itinerary Page






Personalised Business Trip Itinera
https://joshryan212.wixsite.com/ryans-travel/personalised-business-trip-itinerar
This site was designed with the WIX.com website builder. Create your website today.
Start Now
What Activities and Entertainment would you like to do while on your Business Trip?
Sports:
Entertainment:
1: Water Sports, 2: Athletics, 3: Ball Sports, 4: Combat Sports, 5: Winter Sports, 6: A Mix
1: Nightlife/Dance Clubs, 2: Festivals 3: Fairs, 4: Films, 5: Music, 6: Fashion, 7: Comedy, 8: A Mix oof Everything, 9: None
Where and How would you like eat while Away?
Frequency of Eating Out:
Cuisine:
Let's Chat!


Personalised Business Trip Itinera
https://joshryan212.wixsite.com/ryans-travel/personalised-business-trip-itinerar
This site was designed with the WIX.com website builder. Create your website today.
Start Now
Frequency of Eating Out:
Cuisine:
1: Multiple Times a Day, 2: Once a Day, 3: Once Every 2 Days, 4: 2-3 Times a Week, 5: Once a Week
1: Ethnic, 2: Fast Food 3: Fast Casual, 4: Casual Dining, 5: Premium Casual, 6: Family Style, 7: Fine Dining
AI Powered Personlised Itinerary
GO
500 Terry Francois Street
San Francisco, CA 94158
info@mysite.com
Tel: 123-456-7890
Fax: 123-456-7890
Name
Email
Subject
Message
Submit
© 2023 by Bon Voyage. Proudly created with Wix.com
Let's Chat!

Appendix F: Ryan’s Travel Website - Personalised Holiday Itinerary

Travel Itinerary

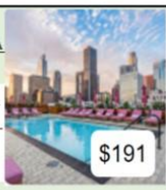
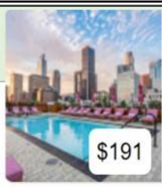
Trip Overview

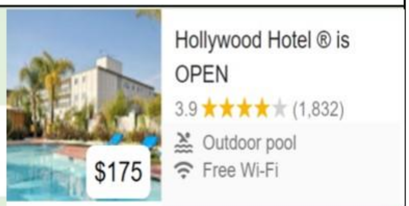
Trip Start Date	23rd of March, 2021
Trip End Date	30th of March, 2021
Duration (Days)	8
No. of Travelers	2

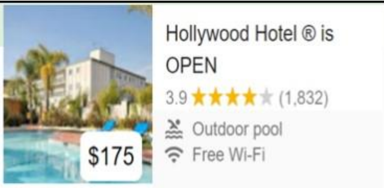
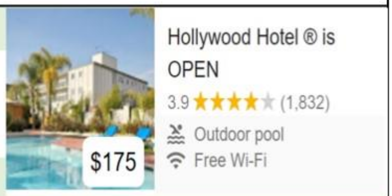
List of Travelers

Name

Trip Itinerary

Date	Area Of The City	Activities	Location	Hotel
Tuesday 23rd	Downtown LA	Check in to Freehand Los Angeles hotel (30 minute Drive)	416 W 8th St, Los Angeles, CA 90014	 Freehand Los Angeles 4.3 ★★★★★ (1,729) Outdoor pool Free Wi-Fi
Morning	Hollywood Heights	Visit the TCL Chinese Theatres (20 Minute drive)	6925 Hollywood Blvd, Hollywood, CA 90028	
Afternoon	Hollywood Heights	Lunch at Tiago Coffee Bar & Kitchen (7 Minute walk) Shopping at Hollywood & Highland (6 Minute walk)	7080 Hollywood Blvd, Los Angeles	
Night	Downtown LA	Dinner at Badmaash, then watching a basketball game at the Staples Center	108 W 2nd St Apt 104 Los Angeles, CA 90014 1111 S Figueroa St, Los Angeles,	
Wednesday 24th	Downtown LA	Breakfast at Freehand LA Hotel	416 W 8th St, Los Angeles, CA	 Freehand Los Angeles 4.3 ★★★★★ (1,729) Outdoor pool Free Wi-Fi
Morning	Murphys Ranch	Visit a rundown history filled abandoned Nazi base founded by Norman Stephens in the 1930's	Sullivan Fire Rd, Pacific Palisades, CA 90272	
Afternoon	Santa Monica	Santa Monica Beach for some lunch and exploring (20 Minute drive) Shopping at the local Santa Monica Markets and Santa Monica Place	395 Santa Monica Pl, Santa Monica, CA 90401	
Night	Santa Monica	Dinner at Citrin, Then explore some of the numerous bars in Santa Monica	114 E 2nd St Los Angeles, CA 90012	

Thursday 25th	Downtown LA	Breakfast at Freehand LA Hotel, check out of hotel, 6 minute walk to Shearton Grand Hotel, Check in laguage	711 S Hope St, Los Angeles, CA 90017	
Morning	Balboa Island	Paddle Boarding around Balboa Island (1 Hour drive	1500 W Balboa Blvd #101, Newport Beach, CA 92663	
Afternoon	Balboa Island	Lunch at Wilma's Patio Restaurant. Then visit the Balbo Island Museum	203 Marine Ave, Newport Beach, CA 92662	
Night	Redbird / Eagle Rock	Dinner any where in the Redbird Dining Scene. After Dinner, visit Street Food Cinema Drive-in	114 E 2nd St Los Angeles, CA 90012 1617 Colorado Blvd, Los Angeles, CA 90041	
Friday 26th	Downtown LA	Breakfast at Sheraton Hotel, Then a 20 minute drive to the Hollywood Bus Tour		
Morning	Hollywood	Hollywood Bus tour, visit all famous LA sites including: the Hollywood Sign, Walk of Fame, etc. (4 hours tour)	6333 W 3rd St, Los Angeles, CA 90036	
Afternoon	Glendale	Lunch and Shopping at Glendale Galleria	100 W Broadway Suite 100, Glendale, CA 91210	
Night	Downtown LA	Dinner at 71Above, Then explore some of the numerous bars in DT LA	633 W 5th St, Los Angeles, CA	
Saturday 27th	Downtown LA	Breakfast at the Sheraton, Check out and come back for bags later.		
Morning	Downtown LA	Visit Hauser & Wirth Art Gallery (10 minute drive)	909 E 3rd St, Los Angeles, CA 90013	
Afternoon	East Hollywood / Griffith Park	Check in to Hollywood Hotel ® (12 minute drive). Visit Griffith Park, (Choose to visit the LA Zoo, Griffith Observatory, Autry Museum of the American West, etc)	1160 N Vermont Ave, Los Angeles, CA 90029, 4730 Crystal Springs Dr, Los Angeles, CA 90027	
Night	East Hollywood	Dinner at Bianca's Deli, Then visit the Laugh Factory for a comedy show	1307 N Vermont Ave B, Los Angeles, CA 90027 8001 Sunset Blvd, Los Angeles, CA 90046	

Sunday 28th	East Hollywood	Breakfast at Hollywood Hotel ®		
Morning	Joshua Tree National Park	Visit Joshua Tree National Park, enjoy the two different desert ecosystems combine. Have lunch at National Park (1.5 hour drive each way)		
Afternoon	Dockweiler Beach	Have dinner at one of the many restaurants around Dockweiler Beach	12000 Vista Del Mar, Playa Del Rey, CA 90293	
Night	Dockweiler Beach	Go down to Dockweiler Beach for bonfires and to watch the sunset.	12000 Vista Del Mar, Playa Del Rey, CA 90293	
Monday 29th	East Hollywood	Breakfast at Hollywood Hotel ®		
Morning	Venice Canals	Visit the Venice Canals a historical district with plenty to explore (31 minute drive.)	Venice, CA 90292	
Afternoon	Venice Beach	Have Lunch at James' Beach Restaurant	60 N Venice Blvd, Venice, CA 90291	
Night	Venice Beach	Have dinner at the High Rooftop Lounge in Hotel Erwin, experience the nightlife that Venice Beach provides	1697 Pacific Ave, Venice, CA 90291, United States	

Flight Details	Depart from: Oklahoma at 5.48am on the 23rd of March 2021, land in Dallas at 7am (1h 12m Flight). 40 minutes lay over, depart Dallas at 7.40, arrive in Los Angeles Ontario Intl. at 8.40 Local Time (3h Flight). Flying with America Airlines for $112 One way.
Return Flight Details	20 Minute Taxi to LAX Airport on the 30th of March 2021 for a 6.45am Flight to Phoenix. Arrive in Phoenix at 8.10am (1h 24m Flight), 48 Minute lay over. Leave Phoenix at 8.48am, arrive in OKC at 1.21PM local time (2h 24m Flight) Flying with American Airlines, $142

Appendix G: Ryan's Travel Website - Personalised Business Trip Itinerary

Business Trip Itinerary

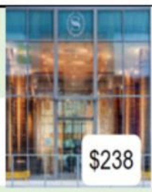
Trip Overview

Trip Start Date	Please Enter
Trip End Date	Please Enter
Duration (Days)	4
No. of Travelers	3

List of Travelers

Name

Trip Itinerary

Date	Area of the City	Activities	Location	Hotel
Day 1	Downtown LA	Breakfast at the Sheraton Hotel	711 S Hope St, Los Angeles, CA 90017	 Sheraton Grand Los Angeles 4.4 (1,910) Outdoor pool Free Wi-Fi
Set Business Hours 9am-4pm				
After 4pm	Santa Monica	Dinner at Citrin	114 E 2nd St Los Angeles, CA 90012	
After Dinner	Santa Monica	Explore the numerous bars in Santa Monica, just a small walk from Citrin	115 E 2nd St Los Angeles, CA 90012	
Day 2	Downtown LA	Breakfast at the Sheraton Hotel	711 S Hope St, Los Angeles, CA 90017	 Sheraton Grand Los Angeles 4.4 (1,910) Outdoor pool Free Wi-Fi
Set Business Hours 9am-4pm				
After 4pm	Downtown LA	Dinner at Badmaash	108 W 2nd St Apt 104 Los Angeles, CA 90014	
After DInner	Downtown LA	Visist the Staples Center for an NBA Basketball game	1111 S Figueroa St, Los Angeles, CA 90015	

Day 3	Downtown LA	Breakfast at the Sheraton Hotel	711 S Hope St, Los Angeles, CA 90017	
Set Business Hours 9am-4pm				
After 4pm	East Hollywood	Dinner at Bianca's Deli	1307 N Vermont Ave B, Los Angeles, CA 90027	
After Dinner	East Hollywood	After Dinner visit the Laugh Factory for a comedy show	8001 Sunset Blvd, Los Angeles, CA 90046	
Day 4	Downtown LA	Breakfast at the Sheraton Hotel	711 S Hope St, Los Angeles, CA 90017	
Set Business Hours 9am-4pm				
After 4pm	Downtown LA	Dinner at 71	633 W 5th St, Los Angeles, CA	
After Dinner	Downtown LA	30 minute drive to the airport. Return to Oklahoma		

Flight Details	Depart from: Oklahoma at 3.37pm on the 9thrd of October 2020, land in Charlotte at 7.22pm (2h 45m flight). 1-hour lay-over, depart Charlotte at 8.22pm, arrive at New York (JFK) at 10.04pm Local Time (1h 54m Flight). Flying with America Airlines for $195 One way.
Return Flight Details	6.30am Flight to Charlotte. Arrive in Charlotte at 8.32am (2h 2m flight), 53 Minute lay over. Leave Charlotte at 9.25am, arrive in OKC at 10.55PM local time (2H 30m Flight) Flying with American Airlines, $195

Appendix H: Final Questionnaire

Appendix H.a: Block One: Information and Consent

UNIVERSITY OF CANTERBURY
Te Whare Wānanga o Waitaha
CHRISTCHURCH NEW ZEALAND

Understanding Consumer Perceptions of AI

My name is Josh Ryan, I am currently enrolled in a Master of Commerce majoring in Marketing at the University of Canterbury, New Zealand. The purpose of this research is to understand the direct and indirect effects of multiple AI Genders, Purchase Types, and Anthropomorphised Levels, on consumers' cognitive, affective and behavioural response to AI. This research will be conducted using Amazon's Mechanical Turk.

If you are interested in this study, please click on my MTurk advertisement after reading the information below.
If you choose to take part in this study, your involvement in this project will be to participate in an experiment involving answering a few questions, followed by a short video (2 Minutes) that will show a certain type of AI which you will then be questioned on. Participation should take approximately 10-15 minutes; all data will be recorded using Amazon Mechanical Turk's software.

Participation is voluntary and you have the right to withdraw at any stage without penalty. You may ask for your raw data to be returned to you or destroyed at any point. If you withdraw, I will remove information relating to you. However, once the analysis of raw data starts, it will become increasingly difficult to remove the influence of your data on the results. The data will be destroyed after 5 years of the collection of data. A thesis is a public document and will be available through the University of Canterbury Library. To receive the agreed-upon compensation participants are required to complete all parts of this experiment, this includes a measurement of current mood, watch the video and answer the entire questionnaire.

The project is being carried out as a requirement for a master's degree in Commerce by Josh Ryan under the supervision of Paul Ballantine, who can be contacted at **paul.ballantine@canterbury.ac.nz**. He will be pleased to discuss any concerns you may have about participation in the project.
This project has been reviewed and approved by the University of Canterbury Human Ethics Committee, and participants should address any complaints to The Chair, Human Ethics Committee, University of Canterbury, Private Bag 4800,

should address any complaints to The Chair, Human Ethics Committee, University of Canterbury, Private Bag 4800, Christchurch (human-ethics@canterbury.ac.nz).

Department of Management, Marketing and Entrepreneurship

Email: josh.ryan@pg.canterbury.ac.nz

HEC Ref: 650.13

By clicking 'yes' below, you confirm the following:

- You have read and understood the description on the above-named project in the Information Sheet provided.
- On this, basis, you agree to participate as a subject in this project, and consent to the publication of the results of this project with the understanding that your confidentiality will be preserved.
- You understand also that you may withdraw from this project at any time before survey completion.

Yes, I confirm the above statements and would like to take part in this experiment

No thanks

→

Have you been on/or planned a Business Trip/Holiday in the last 12 months? (this involves either flying or driving to the business trip/holiday destination).

Yes

No

← →

Appendix H.b: Block Two: Users Overall Mood Scale

Please rate the following statements based on your current mood:

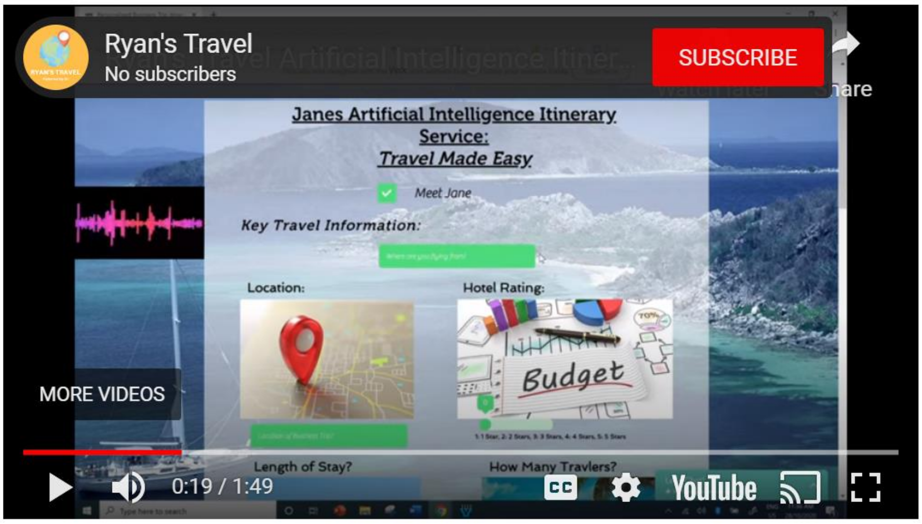
	Definitely do not feel (XX)	Do not feel (X)	Slightly feel (V)	Definitely feel (VV)
I am feeling Lively				
I am feeling Happy				
I am feeling Sad				
I am feeling Tired				
I am feeling Caring				
I am feeling Content				
I am feeling Gloomy				
I am feeling Jittery				
I am feeling Drowsy				
I am feeling Grouchy				
I am feeling Peppy				
I am feeling Nervous				
I am feeling Calm				
I am feeling Loving				
I am feeling Fed up				
I am feeling Active				

Appendix H.c: Block Three: Stimuli Exposure

Please read the following Scenario:

Imagine you are planning your next business trip; you are looking to fly to Las Angeles. The purpose of this trip is purely for business purposes and you expect a dull and tedious trip, which isn't an issue as you will be busy throughout most of the day. In saying this you are still unsure what activities or experiences you should have while there. Fed up with traditional work-related travel agencies and tour operator services you decide to use Ryan's Online Travel Service for the first time to plan and book your upcoming business trip. Ryan's Travel offers a booking capability that utilises Artificial intelligence to plan a personalised itinerary for people looking to plan their business trip. The software will ask a variety of questions to determine your business trip needs, wants and expectations; to create a structured, organised and well-planned itinerary. Your information will then be analysed and used in conjunction with millions of previous travel itineraries and information found online to match your personal preferences with accommodation and activities. After you accept your day by day personalised itinerary, Ryan's Travel will book all flights, accommodation and activities for you and your travelling party, saving hours of time and hassle.

Please watch the video below



Please select the AI's Name.

Jane | Joe | John | Josh | Nathan | Henry | Elizabeth

What was the purpose of the travel itinerary?

To plan a personlised business trip | To plan a birthday party | To plan a wedding | To plan a business function | To plan a personlised holiday

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Appendix H.d: Block Four: Manipulation Checks

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What did you think of the humanised validity of the AI Voice during your experience with Ryan Travels itinerary service?

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I considered the AI voice to be masculine.	○	○	○	○	○	○	○
I considered the AI voice to be feminine.	○	○	○	○	○	○	○
The voice I experienced on the website sounded like a male voice.	○	○	○	○	○	○	○
The voice I experienced on the website sounded like a female voice.	○	○	○	○	○	○	○

The purpose of this trip was for:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
This trip is all about pleasurable experiences.	○	○	○	○	○	○	○
This trip will be all about achieving work-related goals.	○	○	○	○	○	○	○

To me, the trip I would be booking via Ryan's Travel AI Itinerary service would be:

Not fun	○	○	○	○	○	○	○	Fun
Dull	○	○	○	○	○	○	○	Exciting
Not delightful	○	○	○	○	○	○	○	Delightful
Not thrilling	○	○	○	○	○	○	○	Thrilling
Not enjoyable	○	○	○	○	○	○	○	Enjoyable
Tedious	○	○	○	○	○	○	○	Stimulating

Based on the following items, my view on Ryan Travels Artificial Intelligence's was that it appeared to be:

Machinelike	○	○	○	○	○	○	○	Humanlike
Artificial	○	○	○	○	○	○	○	Natural
Not lifelike	○	○	○	○	○	○	○	Lifelike
Robotic	○	○	○	○	○	○	○	Human
Unsophisticated	○	○	○	○	○	○	○	Sophisticated

← →

Appendix H.e: Block Five: Consumer Perception of AI Website

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Based on your experience reading the scenario and your overall experince with Ryan's Travel, please answer the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
This scenario was realistic.	○	○	○	○	○	○	○
This scenario was credible.	○	○	○	○	○	○	○
This scenario was believable.	○	○	○	○	○	○	○

Based on your experience from watching Ryan Travels AI Intinerary service, please respond to the following statements:

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
The experience was believable.	○	○	○	○	○	○	○
The experience was trustworthy.	○	○	○	○	○	○	○
The experience was credible.	○	○	○	○	○	○	○
The experience was reasonable.	○	○	○	○	○	○	○
The experience was convincing.	○	○	○	○	○	○	○
The experience was unbiased.	○	○	○	○	○	○	○
Please enter strongly agree.	○	○	○	○	○	○	○

How involved did you feel during your experience with Ryan Travels AI itinerary service?

Not involved at all	Not involved	Somewhat not involved	Neither involved nor not involved	Somewhat involved	Involved	Very involved

How interested did you feel during your experience with Ryan Travels AI itinerary service?

Not interested at all	Not interested	Somewhat not interested	Neither interested nor not interested	Somewhat interested	Interested	Very interested

How engaged did you feel during your experience with Ryan Travels AI itinerary service?

Not engaged at all	Not engaged	Somewhat not engaged	Neither engaged nor not engaged	Somewhat engaged	Engaged	Very engaged

What Sense of Presence did you feel during the AI video?

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
Your sense of presence was strong while watching Ryan Travels AI video.	○	○	○	○	○	○	○
Your sense of “being there” was strong while watching Ryan Travels AI video.	○	○	○	○	○	○	○
Your sense of inclusion was strong while watching Ryan Travels AI video.	○	○	○	○	○	○	○

← →

Appendix H.f: Block Six: Consumer Attitude Towards AI

How helpful did you think this AI would be at planning a holiday/business trip?

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
The AI was informative.	○	○	○	○	○	○	○
The AI was useful.	○	○	○	○	○	○	○
The AI was helpful.	○	○	○	○	○	○	○

Would you use this/or a similar AI Travel Agency service in the future?

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
If given a chance, I think ill use this software in the near future.	○	○	○	○	○	○	○
If given a chance, I'm certain to use this software in the near future.	○	○	○	○	○	○	○
If given a chance, I plan to use this software during the near future.	○	○	○	○	○	○	○

After experiencing Ryan Travels AI itinerary service, how likely are you to purchase/use this type of software in the future?

	Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely
How likely is it that you would return to Ryan Travel's website?	○	○	○	○	○	○	○
How likely is it that you would consider using Ryan Travels services in the short term? (within the next 3 months)	○	○	○	○	○	○	○
How likely is it that you would consider using Ryan Travels services in the longer term? (within the next year)	○	○	○	○	○	○	○
For the purchase used in this example, how likely is it that you would use Ryan Travels services?	○	○	○	○	○	○	○

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Appendix H.g: Block Seven: Demographics

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What is your Gender?

Male	Female	Prefer not to say	Other (please specify)

What is your Age?

18 - 24	55 - 64
25 - 34	65 - 74
35 - 44	75 - 84
45 - 54	85 or older

What is your Ethnicity?

- Caucasian
- Hispanic American
- African American
- Native Hawaiian
- American Indian
- Other (please specify)
- Asian American

What is your highest form of Education?

- Some High School
- Master’s Degree
- High School Diploma
- PhD or Doctorate Degree
- Bachelor’s Degree
- Other (please specify)

What is your Occupation?

Employed full time	Student
Employed part time	Disabled
Unemployed looking for work	Prefer not to say
Unemployed not looking for work	Other (please specify)
Retired	

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Survey Code: 2121
Please enter this code into Mechanical Turk to complete your HIT.

Please ensure you click next one more time to submit your responses before returning to MTurk.

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